

AGE AWARE POWER ALLOCATION FOR ENERGY-EFFICIENT WIRELESS NETWORKS USING RSMA

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By
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Age Aware Power Allocation for Energy-Efficient Wireless Networks
using RSMA

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We certify that we have read this thesis and that in our opinion it is fully adequate,
in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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With the commercial deployments of 5G, research in Beyond 5G (B5G) and 6G networks has started. Within the context of meeting all needs and demands of future generation networks, the predicted usage is envisaged in three cases: massive Machine-Type Communications (MTC), ultra-reliable low-latency communications, and enhanced mobile broadband. This thesis focuses on massive Machine-Type Communications (mMTC).

Energy efficiency, under the banner of green communications and networking is one of the branches complementary to the research conducted on MTC. mMTC, industrial and medical Internet of Things (IoT) type technologies will demand not only networking capabilities for massive access, enhanced communications, but also sustainability and power efficiency. Rate Splitting Multiple Access (RSMA) presents a candidate massive access scheme with spectral efficiency, energy efficiency, reliability, Degree-of-Freedom (DoF) and Quality of Service (QoS) enhancements in most of user deployments and network loads over traditional access schemes used in 5G. Within the scope of the thesis, we propose an age-aware power allocation policy for minimizing the network's Weighted-Sum Average AoI (WSAoI). To our knowledge, this is the first work in the literature which combines the Age of Information (AoI) concept and RSMA framework.

For downlink communication, we formulate the network's WSAoI minimization as a Markov Decision Process (MDP) and investigate an optimal as well as suboptimal policies for the Base Station (BS) to select a scheme among RSMA, Orthogonal Multiple Access (OMA), and Nonorthogonal Multiple Access (NOMA). We prove existence of an optimal policy. Complexity of computation is reduced by using an action elimination technique, and by using a

sub-optimal policy with performance close to the optimal. We also investigate the tradeoff between energy and the WSAoI of the network. The adaptive RSMA only scheme outperforms adaptive RSMA/NOMA/OMA and OMA/NOMA on the basis of network's WSAoI. For example, when RSMA is selected, the performance metric, WSAoI, at 14, 15, and 16 dB SNR values, is on average, respectively 35.8%, 15.7%, and 12.7% less than the NOMA/OMA cases. Overall, it is seen that, the optimum policy becomes more likely to operate in the RSMA mode with an increase in Signal to Noise Ratio (SNR). By using RSMA scheme instead of NOMA/OMA scheme, power consumption can be saved in average 65.8%, 62.3%, and 59.6% for the selected WSAoI values of 4, 3, and 2, respectively.

Keywords: Age of Information, Wireless Networks, Massive Machine-Type Communications.

ÖZET

RSMA KULLANAN ENERJİ-VERİMLİ KABLOSUZ AGLAR İÇİN BİLGİ YAŞINA DUYARLI GÜÇ TAHSİSİ

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5G'nin ticari kullanımları ile, 5G ötesi ve 6G ağlara ilişkin araştırmalar başlatılmıştır. Gelecek nesil ağların ihtiyaç ve taleplerini karşılama kapsamında, öngörülen kullanım üç kullanım durumu olarak beklenilmektedir: yoğun Makine-Tipi Haberleşme (MTC), yüksek-güvenilir düşük-gecikmeli haberleşme, ve geliştirilmiş taşınabilir geniş bant. Tez, yoğun Makine-Tipi Haberleşme (mMTC) kullanım durumuna yoğunlaşmaktadır.

Yeşil haberleşme ve ağ oluşumu başlığı altında araştırılan tüketimi azaltmaya yönelik enerji verimliliği; Yoğun Makine Tipi Haberleşme araştırmalarının tamamlayıcı alt alanlardan biridir. Yoğun Makine Tipi Haberleşme, endüstriyel ve tıbbi Nesnelerin İnterneti (IoT) tipi teknolojiler, yoğun giriş için ağ oluşturma yetenekleri ve geliştirilmiş haberleşme yanında sürdürülebilirlik ve güç verimliliğini de gerektirecektir. Veri Hızı Ölçütlemeli Çoklu Erişim (RSMA) üzerindeki araştırma ilerlemesi; geniş ağ yükleri aralığında, 5G'de kullanılan geleneksel giriş şemalarına göre; spectral verimlilik, enerji verimliliği, güvenilirlik, Nitelikli Servis (QoS) ve serbestlik derecesi geliştirmeleri için bir aday yoğun giriş şeması sunmaktadır. Bu tez kapsamında Ağın beklenen Bilgi Yaşı (AoI) ağırlıklı kullanımını en aza indirmek için, bir yaşa duyarlı güç tahsis politikası önermekteyiz. Bu, AoI konsepti ile RSMA çerçevesini birleştiren, bizim dahilinde literatürdeki ilk çalışmadır. Aşağı bağlantı aktarımı için, beklenen AoI kullanımı ağırlıklı toplamının (WSAoI) en aza indirilmesini Markov Karar Süreci (MDP) olarak formüle etmekteyiz ve WSAoI'yı en aza indirmek için, RSMA, OMA, ve NOMA arasında seçim yapacak en uygun baz istasyonu politikasını ve alt uygun politikasını araştırmaktayız. En uygun bir politikanın varlığını kanıtlıyoruz. Hesap karmaşıklığı eylem elemesi, ve en uygun performansa yakın bir başarıyı gösteren bir standart altı politika kullanılarak azaltılmaktadır.

WSAoI ile ağ enerji verimliliği arasındaki dengeyi de araştırmaktayız. Uyarlamalı RSMA şeması, WSAoI açısından, uyarlamalı RSMA/NOMA/OMA ve OMA/NOMA şemalarına göre daha üstün performans göstermektedir. Örneğin, RSMA seçildiğinde, performans ölçüsü olan WSAoI, seçili 14, 15 ve 16 dB SNR değerleri için NOMA/OMA durumuna göre ortalama %35.8, %15.7, ve %12.7 daha iyidir. Ortak ve özel mesajlar için hedeflenen veri hızlarının, WSAoI'yı en aza indiren güç tahsisinde önemli bir rol oynadığı gözlenmektedir. Genel olarak, sinyal gürültü oranı arttıkça politikanın RSMA modunda çalışma olasılığının arttığı görülmektedir. NOMA/OMA yerine RSMA kullanılırsa, güç tüketiminde; seçili 4, 3 ve 2 WSAoI değerleri için ortalama %65.8, %62.3, ve %59.6 tasarruf sağlanabilir.

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List of Abbreviations



ACK	Acknowledgement
ADC	Analog-to-Digital Converter
AoI	Age of Information
BC	Broadcast Channel
BS	Base Station
B5G	Beyond 5G
CDMA	Code Division Multiple Access
CSI	Channel State Information
CSIT	Channel State Information at Transmitter
CTS	Clear To Send
DAC	Digital-to-Analog Converter
DoF	Degree-of-Freedom
EE	Energy Efficiency
eMBB	enhanced Mobile Broadband
FDMA	Frequency Division Multiple Access

IoT	Internet of Things
IRS	Intelligent Reflecting Surface
MAC	Media Access Control
MDP	Markov Decision Process
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
MTC	Machine-Type Communications
mMTC	massive Machine-Type Communications
MTM	Machine-to-Machine Communications
MU-LP	Multiuser Linear Precoding
NCS	Networked Control System
NOMA	Nonorthogonal Multiple Access
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
PHY	Physical Layer
QoS	Quality of Service
RF	Radio Frequency
RS	Rate Splitting
RSMA	Rate Splitting Multiple Access
SC	Superposition Coding
SDMA	Space Division Multiple Access
SE	Signal Efficiency

SIC Successive Interference Cancellation

SINR Signal to Interference and Noise Ratio

SISO Single Input Single Output

SNR Signal to Noise Ratio

TDMA Time Division Multiple Access

URLLC Ultra-Reliable Low-Latency Communications

WSAoI Weighted-Sum Average AoI

1L-RS One Layer Rate Splitting

2L-HRS Two Layer Hierarchical Rate Splitting

List of Symbols

A_{NOMA}	action space for NOMA
A_{RSMA}	action space for RSMA
a_t	sequence of actions at time t
b	$1/\rho$
$C(\pi, s_0)$	policy set with policy π and s_0 initial state
c	$\sum_{j \in K} R_j^{(c)*}$
C_i	i^{th} user's portion of (R_c)
c_i	user i -BS distance
c_o	baseline distance
d	$R_i^{(p)*}$
d_i	normalized distance (c_i/c_o)
h_i	coefficient of channel between the user i and BS
K	number of users
m_c	common status update information for the user i
m_i	status update information for the user i
N	number of actions in action space
n_i	Gaussian noise
P	constant transmission power of BS, transition probability
p	fraction of P used by user (P/N)
p_i	power allocated to user i
P_i^{NOMA}	user i 's outage probability, using NOMA
P_i^{OMA}	user i 's outage probability, using OMA

P_i^{RSMA}	user i 's outage probability, using $RSMA$
R	equal target rate for both users
R_c	common rate
$R_{c,i}$	user i 's common rate
R_i	user i 's target rate
R_i^{OMA}	target rate of user i using OMA
R_i^{NOMA}	target rate for user i using NOMA
R_i^*	target rate for user i using RSMA
$R_i(c)^*$	common target rate of user i using RSMA
$R_i(p)^*$	private target rate of user i using RSMA
r	reward function
S	State space
s_o	initial state
s_t	state in time slot t
α_t	time common power allocation factor indicating the ratio of common message's power to the total transmitted power
$U_i^{(t)}$	latest packet's generation time received by the user i
$v_i^{(t)}$	an indicator showing whether user i receives information (1-receives, 0-does not receive)
y_i	observation at user i
W_i	message of the user i
$W_{c,i}$	common part of W_i
$W_{p,i}$	private part of W_i
W_c	single common message
α_c	total power's fraction for common message
α_i	total power's fraction used for user i 's private message
$\Delta_i(t)$	user i 's instantaneous AoI at time t
$\bar{\Delta}$	time average of instantaneous AoI , weighted sum of the expected age of information
$E[\eta(s, a)]$	expected AoI drop at current state s with action a

γ_i	user i 's SNR
γ_{11}	user 1's received SNR when decoding m_1
γ_{12}	user 1's received SNR when decoding m_2
γ_{22}	user 2's received SNR when decoding m_2
$\gamma_{c,i}$	user i 's SNR in decoding m_c
$\gamma_{p,i}$	user i 's SNR in decoding m_c
π	transmission policy
$\bar{\pi}$	sub-optimal policy
π_t	π at time t
$\lambda_{c,i}$	$R_i^{(c)*}$ to R_i^* ratio
ρ	transmission SNR
τ	path loss distribution
$\Theta_{c,i}$	ratio of C_i to R_c
ω_i	weight coefficient of user i

Chapter 1

Introduction

1.1 General Topic and Background

Concerning the 5G, Beyond 5G (B5G) and 6G networks, the predicted usage is split into three use-cases: enhanced mobile broadband, ultra-reliable low-latency communication, and massive Machine-Type Communication (mMTC). This thesis focuses on mMTC that requires connecting large number of devices in a selected area — up to 1 million devices per square kilometer. Quality of Service (QoS), access and throughput requirements of B5G is vast and they are projected to grow exponentially in the foreseeable future. Exponentially increasing usage of mMTC, medical and industrial IoT type technologies will require enhanced communications and networking capabilities for massive access, and responding to increasing demand for update freshness of the communicated data, and increase of energy efficiency to reduce highly increasing energy consumption (green communications). There is a need for an adaptive policy that will provide fresh data to all of the devices, and that will use the energy with high efficiency.

1.2 Terms and Scope

1.2.1 Terms

Orthogonal Multiple Access (OMA): OMA is a multiple access method with frequency domain sharing among users as shown in Figure 1.1, where U_1 and U_2 portions of the frequency spectrum are allocated to User1 and User2, respectively. Since the users are not served simultaneously by the BS, interference of user messages is not observed, which in turn enables usage of receivers with low-complexity. However, due to orthogonality, OMA cannot support mMTC in 5G and B5G. Some of OMA techniques are Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA), Orthogonal Frequency Division Multiple Access (OFDMA), and Code Division Multiple Access (CDMA) [4].

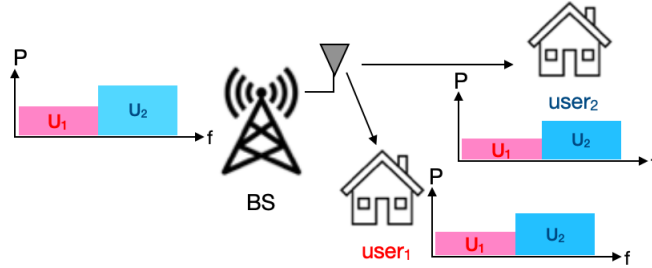


Figure 1.1: OMA in Downlink [1]

Non-orthogonal Multiple Access (NOMA): NOMA is a multiple access method used in 5G wireless network. As shown in Figure 1.2, it can serve multiple users using same frequency/time resources. NOMA, does multiplexing on different power levels or codes. At the transmitter, it uses superposition coding, and allocates different levels of power to each user. Successive Interference Cancellation (SIC) method is used by receiver to retrieve both user's data.

SIC is a method used in wireless data communication, allowing decoding of multiple packets that are transmitted to receiver at the same time. Receiver decodes firstly strongest signal, then subtracts it from combined signal. The difference is decoded as weaker signal. This process continues till all are decoded,

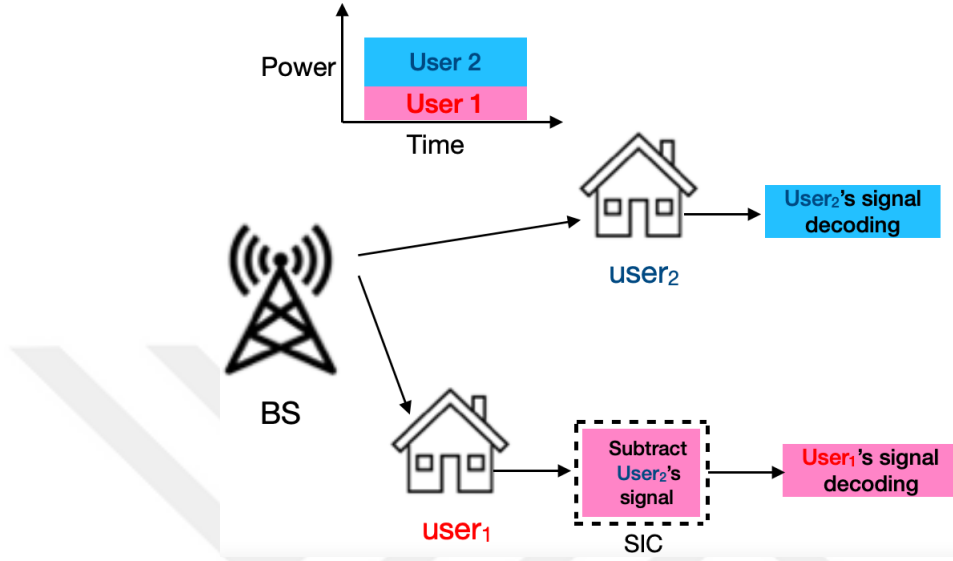


Figure 1.2: NOMA in Downlink [2]

as sketched in Figure 1.3. In NOMA, at near user (User1), far user (User2)'s signal is subtracted by using SIC technique, and then User1's signal is decoded. At the User2 (far user) side, signal of User1 is treated as noise and User2's signal is decoded directly [4].

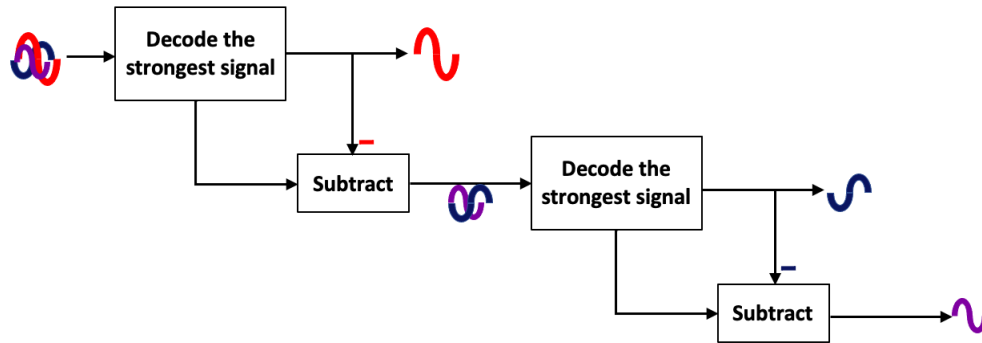


Figure 1.3: Successive Interference Cancellation (SIC)

There are some drawbacks of NOMA in comparison to OMA:

- OMA has limited user capacity. NOMA can serve multiple users simultaneously by allocating “non-orthogonal” resource. However, support of extra users is achieved through an increase in receiver complexity. Non-orthogonality of resources yields to an additional challenge of inter-user

interference. Using a scheme to eliminate the interference increases the receiver complexity substantially.

- Each user in a cluster needs to decode not only its own message but also all other users' messages. This increases receiver's complexity and power consumption.
- OMA schemes limit number of users connecting simultaneously. However, when an error occurs due to SIC in one user, information of the other users will be decoded erroneously, which will limit users that can served by the cell of each cluster. At the receiver, to be able to use power domain functionality in NOMA, there should be sufficient channel gain difference of users. The clusters' served user pairs will be limited due to this constraint.

Rate Splitting Multiple Access (RSMA): RSMA is a multiple access scheme using linearly precoded RS at transmitter and SIC at receivers so that it decodes part of interference, and handles as noise remaining part, which is promising for QoS and rate. At the transmitter, user messages are separated as private and common [3]. Common messages are combined and encoded to common streams. Later, they need being decoded by many users. However, private messages are encoded to private streams so that they should be decoded by only the related users. At receiver, each user decodes common streams, applies SIC, and decodes its own private stream. Then, each user merges its own private and common messages to get original message.

RSMA is a general multi-user transmission scheme which includes OMA, NOMA as its special cases. RSMA reduces to NOMA if channels are properly aligned and show the required diverse strengths [3].

RSMA is explained in Figure 1.4 for a two-user transmission. Messages of rear and far users are, W_1 and W_2 . At transmitter, the messages are split by message splitter as common part and private part, namely $[W_1^c, W_1^p]$ for rear user and $[W_2^c, W_2^p]$ for far user. The common parts, W_1^c, W_2^c , are combined by message combiner as W_{12} . W_{12} is encoded to common stream s_{12} through the coding known by the related users, which is later decoded by these users. Private

parts, W_1^p and W_2^p , are encoded to relevant private streams s_1 and s_2 . The streams $s = [s_1, s_{12}, s_2]$ are precoded linearly as $P = [p_1, p_{12}, p_2]$. The transmit signal is $x = P.s = p_{12}.s_{12} + p_1.s_1 + p_2.s_2$, which has two parts: one for User 1, $x_1 = p_{12}.s_{12} + p_1.s_1$, and one for User 2, $x_2 = p_{12}.s_{12} + p_2.s_2$. At the users side, the receive signal is $y = P.\hat{s} = p_{12}.\hat{s}_{12} + p_1.\hat{s}_1 + p_2.\hat{s}_2$, which has two parts: one for User 1 (rear user), $y_1 = p_{12}.\hat{s}_{12} + p_1.\hat{s}_1$, and one for User 2 (far user), $y_2 = p_{12}.\hat{s}_{12} + p_2.\hat{s}_2$. At rear user side, rear user decodes $\hat{s}_{12}$ through accepting interference of $\hat{s}_1$ and $\hat{s}_2$ as noise. Rear user decodes part of interfering far user's message. Once $\hat{s}_{12}$ is successfully decoded, we get $\hat{W}_{12}$ at rear user's side. As $\hat{s}_{12}$ is decoded, its contribution to y_1 is subtracted to get $\hat{s}_1$. Then, User 1 decodes its private stream s_1 into $\hat{W}_1^p$. Then $\hat{W}_1^c$ and $\hat{W}_1^p$ of User 1's message are combined into the message for User 1 as $\hat{W}_1$. The same procedure is applied for User 2, in parallel to the procedure for User 1.

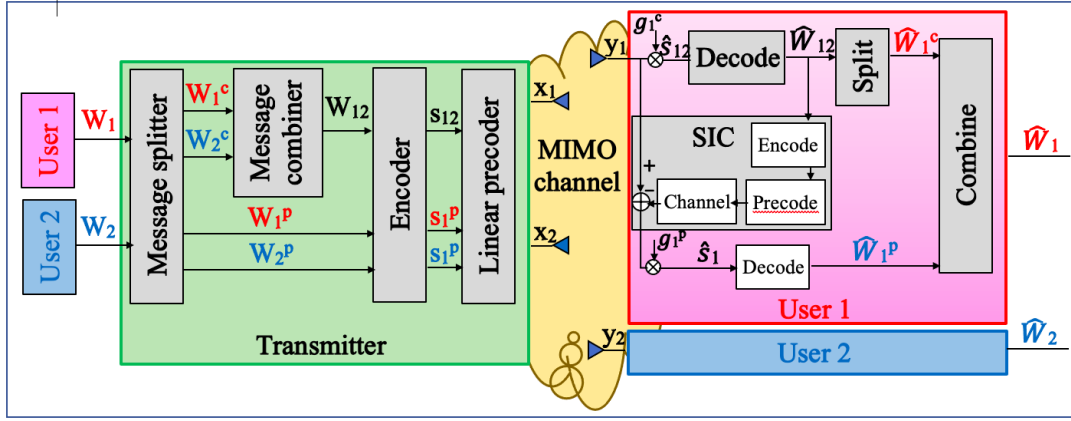


Figure 1.4: Two-user transmission model using RSMA [3]

RSMA fills in the drawbacks of NOMA:

- RSMA performance is obtained with transmitter and receiver having less complexity in comparison to NOMA which requires complicated user grouping, dynamic switching between Space Division Multiple Access (SDMA) and SC-SIC, and multiple SIC layers. However, even a one layer RS and a single layer SIC might outperform NOMA [3].
- Since RSMA contains NOMA and OMA as sub-schemes, its energy and spectral efficiency is better than available multiple access policies.

- Moreover, RSMA is a versatile scheme that can be applied to various users and network load levels since it can easily switch to different schemes, e.g. SDMA and NOMA [4].

Wireless network generations are shown schematically in Figure 1.5. This figure illustrates basic working principles of the schemes in a comparative way.

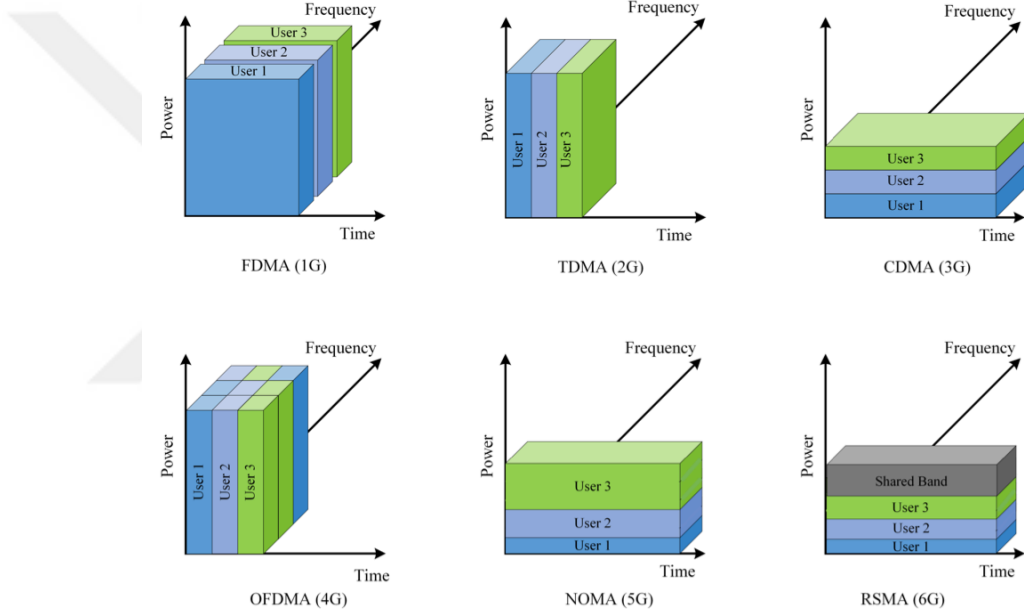


Figure 1.5: Multiple Access Schemes [4]

1.2.2 Scope

Wireless communications between multiple Base Stations (BS) and the related users is bidirectional; namely from BS to users (down-link transmission) and from the users to BS (uplink transmission).

Under normal conditions, it is expected that a user communicates with the closest BS. For simplicity, the communication system can be confined to one BS-multiple user communications as shown in Figure 1.6.

Although there are K users communicating with BS, for simplicity, we consider

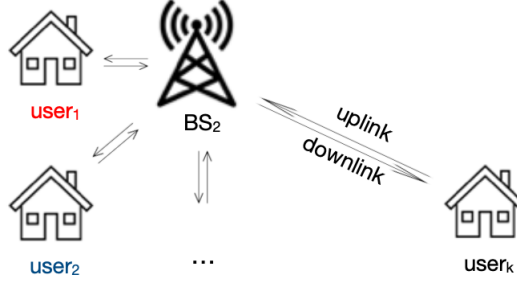


Figure 1.6: Downlink and Uplink Transmission

two-user case that are at different distances to the BS.

This thesis focuses on the mMTC use where BS transmits to two users such that user1 is closer to BS than user2, i.e., two-user downlink scenario.

1.3 Motivation of the Thesis

- QoS, access and throughput requirements of B5G is vast. In the recent few years, the number of personal, health care, and industrial IoT devices has grown exponentially, and is projected to grow exponentially in the foreseeable future. This will increase the energy consumption.
- Nonorthogonal Multiple Access (NOMA) is commonly stated as an alternative for 5G. Therefore, the existing research attempts are also on energy efficient NOMA, referred to as green NOMA, and one of the trending scheme proposed for green NOMA is AoI [5]. AoI is elapsed time since generation of successfully received last message [6]. With the increasing network traffic, overall timeliness of the network-wide information, Weighted Sum of Expected AoI (WSAoI), becomes a key issue.
- In literature, general emphasis is on OMA and NOMA, and superiority of NOMA over OMA. There seems to be a lack of emphasis on other power domain nonorthogonal transmission strategies such as RSMA. Clerckx et al [7] show that NOMA underperforms compared to Multiuser Linear Precoding (MU-LP), the basic principle behind SDMA and RS, and NOMA

has a higher receiver complexity. As the inefficiency of NOMA in multiple antenna networks is discussed, RSMA is suggested for future downlink communications [7]. In addition, recent studies refer to RSMA as the promising strategy for B5G [8],[9]. There are also performance analysis of RSMA for the emerging technologies for the next generation wireless networks [10]. mMTC has increased energy consumption, and energy consumption is expected to grow considerably in near future. Therefore, 6G brings power optimization and energy efficiency under spotlight. Overall, our motivation is directed towards the analysis and comparison of RSMA as a candidate for future generation networks with the existing multiple access schemes. We make our research on the results about an optimal policy based on RSMA/NOMA/OMA that will minimize WSAoI-used to measure timeliness of the network-wide information, age-energy trade-off, and energy efficiency, spectral efficiency of RSMA compared to NOMA and OMA.

1.4 Contributions

We consider a wireless communication between a BS and multiple users. BS conducts transmission in time slots. BS can switch between RSMA, OMA and NOMA so that information freshness of the network, defined by AoI [5], is minimized. In OMA, BS can serve only one user at a time, and it decides which user to be served in the time slot considered. In RSMA and NOMA, more than one user might be served simultaneously, and BS decides power level to be allocated to each user.

We study a two-user downlink scenario. We formulate the minimization of WSAoI as a MDP. We define an optimal policy to minimize network's WSAoI. We base the policy on instantaneous AoI of the users. BS decides on the transmission scheme to be used. Computation complexity of optimal policy is high, and it requires high computation time. Computation time can be reduced by applying an action elimination technique. Due to computation complexity and high computation time of optimal policy, a suboptimal policy with less computation

complexity and time is also defined. Sub-optimal policy results are very close to results of optimal policy especially at close user distances to BS, and at high SNR values.

We analyze AoI metric in RSMA mode. To our knowledge, this is the first work in literature combining AoI and RSMA scheme.

We analyze RSMA parametrically in terms of WSAoI and age-energy trade-off, under various simulation scenarios defined by using different combinations of the selected five parameters, and compare simulation results with results of NOMA/OMA. We study effect of five parameters on adaptive policy and age-energy trade-off: user target rate, user common target rate, user weight, user distance to BS, and SNR.

- The adaptive RSMA only scheme outperforms adaptive RSMA/NOMA/OMA and OMA/NOMA schemes in terms of the WSAoI of the network. For example, when RSMA is selected, the performance metric, WSAoI, at SNR levels of 14, 15, and 16 dB, is in average respectively 35.8%, 25.4%, and 18% less than the NOMA/OMA cases.
- By using RSMA scheme instead of NOMA/OMA scheme, power consumption can be saved in average 65.8%, 62.3%, and 59.6% for the selected WSAoI values of 4, 3, and 2, respectively.
- Motivated by the results of RSMA, we highlight the potential of RSMA as a massive scheme that can be considered as a candidate for B5G.

1.5 Outline

Following chapters are organised as follows. In Chapter 2, first of scheduling problems is considered. Then, the system model for downlink system is studied where rate expressions, AoI analysis, outage probabilities are given in Chapter 3. Based on expressions and the analysis, a minimization problem is defined. In Chapter 4, the policy to minimize WSAoI is studied. In Chapter 5, numerical results for all the scenarios that parametrically analyze effect of each parameter on the performance metrics of WSAoI and age-energy tradeoff are given. Finally, Chapter 6 provides conclusions and recommendations for future.

Chapter 2

Literature Review

This chapter explores use-cases of future generation networks and work from literature that is related to RSMA and AoI.

2.1 Massive MTC

Research on 5G wireless networks offers potential use cases to industrial applications. Desire for remote access and control of industrial facilities might yield to novel applications, such as telerobotics, remote control and monitoring. Most of the considered scenarios are on Networked Control System (NCS) through a communication medium. Considering the performance metrics of NCS, there is need for networking policies not to degrade the performance with increasing demands. 5G networks are envisaged to support Machine-to-Machine Communications (MTM) or MTC referring to applications with data communications between mobile systems. Energy grids, process automation, smart houses, and health care applications are examples of MTM / MTC in 5G and B5G cellular networks. According to [11], scheduling draws attention, if it is related to event or time-trigger based control. Nature of wireless channels is variable. Various control loops require trade-offs. In a network, there might be multiple traffic

types. Considering all these fact, to achieve gain, control metrics for network design should be defined. In particular, a performance metric raises interest; that is AoI. AoI is a newly defined metric for measuring information freshness of network operations done by using sensor applications.

2.2 Rate Splitting Multiple Access

RSMA, a code division multiple access method, is originated with the purpose of serving multiple users simultaneously. It is a physical layer strategy that uses RS concept. RSMA is a bridging method between fully handling interference as noise and full decoding of interference. Instead, it treats partially interference as noise, and decodes partially interference. For future wireless networks, RSMA seems to a new solution to non-orthogonal transmission and massive access.

In old studies, RSMA is called as Rate Splitting (RS) where each user's message is divided into private and common. This method creates the backbone of RSMA multiple access scheme. RSMA is first suggested as a technique for multi user multiple access channels. RSMA can reach any point the capacity region with polymatroid properties. It is shown in [12] that RSMA may achieve every point of its capacity at relatively low coding complexity. It does not require coordination among the transmitters.

Each user except one is first split to virtually two users. The associated splitting coefficients is denoted as $\epsilon = (\epsilon_1, \dots, \epsilon_N)$. For a user i , if $\epsilon_i(1 - \epsilon_i) \neq 0$, its power is split into two parts, $\epsilon_i P_i$ and $(1 - \epsilon_i) P_i$, each of which corresponds to a virtual user. A decoding order π of the virtual users is found to realize the objective rate tuple by successive decoding. [13] proposes an algorithm for computing splitting parameters.

RSMA concept mentioned in [12, 13] was as a multiple access technique. Recently, RSMA refers to a multiple access scheme which is developed with a consideration of MISO broadcast channel [3]. Throughout the thesis, it is referred to the latter scheme. For B5G and 6G communication systems, RSMA, as a multiple access framework, is shown to have probability to replace MAC and PHY layer designs.

2.2.1 Rate Splitting Multiple Access in Multi-Antenna Downlink Communication Systems

For downlink multiantenna systems, RSMA is a versatile multiple access scheme containing SDMA and NOMA as special cases. RSMA decodes interference partially, and handles remaining part as noise by using RS and SIC. This approach improves QoS, rate and reduces complexity.

Mao et al [3] name their newly proposed method as RSMA. They compare RSMA with NOMA and SDMA. They solve Weighted Sum Rate maximization problem in Broadcast Channel (BC)-MISO. They investigate Channel State Information at Transmitter (CSIT). They use Weighted Minimum Mean Squared Error to solve the problem. They show limitations of NOMA and SDMA as CSIT inaccuracy, lack of robustness to network load and user deployments. They propose to transmit common symbols to be decoded by different users on private symbols to be decoded by only related users. They show that, by decoding interference partially and handling other partial as noise, RSMA outperforms NOMA and OMA in terms of network load, CSIT inaccuracy, and user deployments. It is shown that some forms of RS, One Layer Rate Splitting (1L-RS) and Two Layer Hierarchical Rate Splitting (2L-HRS), are successful in reducing receiver and scheduler complexity. 1L-RS is recommended as alternative to SIC-Superposition Coding (SC) in a Single Input Single Output (SISO) BC deployment.

By using link level simulation, RSMA is shown to be more robust and provide substantial throughput superiority over NOMA and SDMA in a MISO BC downlink setting under imperfect CSIT [14].

Chen et al [15], by using precoded overload scenarios, study a problem of optimization for RS based transceiver. For transmitter and receiver, they find the precoder and the equalizer that solve the fairness optimization problem respectively. They generate a system using a 4G/5G link level simulator, on which the authors add RS based block components. Results of simulation illustrate that the achievable rate of their approach is non-saturated, since RS-based method is using less antennas compared to the conventional precoder without RS. The authors investigate also the system's performance for uncoded link level. Through using Bit Error Rate performance, the authors show that Bit Error Rate error floor may reflect saturation rate.

The authors consider various algorithms of decoding for the system based on RS, with the idea that the users with interference-limited private rate limit Bit Error Rate performance, causing error floor. To solve the problem, the authors propose changing decoding algorithm, through cancelling of private messages that are poorly decodable.

According to study made by Cai et al [16], RSMA seems to be better also in achieving high spectral efficiency in comparison to OMA and NOMA. They study, in addition to maximizing Weighted Sum Rate, Secrecy Sum Rate maximization with a multiple-antenna eavesdropper system having Artificial Noise. They develop a secure transmission system that is based on RSMA, with the goal of achieving security enhancement and developing an adaptive beamforming. For maximization of Secrecy Sum Rate, they formulate rate allocation, power optimization, and design of beamforming, with the constraints of power limit of Base Transceiver Station, and the successful SIC requirement.

Yang et al [17] investigate SISO RSMA system for allocating common message

rate's data rate and transmitting power for private and common messages. They formulate the issue as maximization of a sum-rate. They derive a closed form for finding private message's optimum power of transmit. For this issue, they define a solution space in finite form. At the end, they propose a search algorithm in one dimensional form for finding power control solutions and allocating optimum rate. It is shown with simulations that RSMA provides better sum rate in comparison to OFDMA and NOMA. In addition, Yang et al extend their study to SISO and MISO RSMA systems in [18] and introduce SIC constraints in addition to rate constraints.

The RSMA with SIC constraint is found out to attain a greater sum-rate in comparison to the case without constraint of SIC. It is also shown that, in comparison to RSMA, NOMA's and OFDMA's sum-rates decline more quickly when the minimum target rate increases. This is because sensitivity of NOMA and OFDMA to demand for minimum rate are less in comparison to RSMA in SISO case, although RSMA has a higher spectrum efficiency than RSMA/NOMA scheme. RSMA, for the sum-rate, outperforms NOMA when there is a strong demand for the maximum rate and a low maximum transmit power. The reason of this observation is that RSMA dynamically distributes data rate used for common messages to a number of users to fulfill rate demand, whereas in NOMA, the rate is allotted to a single user.

Su et al [19] propose Signal and Interference Alignment transmission scheme that is based on RS. Through using outage probability, Symbol Error Rate, and average sum rate formulae, they analyze performance with CSIT quantization error at high values of SNR. They revealed a relationship between RS and Interference Alignment.

Su et al [19] show that, since common part of the message does not depend on accuracy of CSIT, conventional transmission can be improved significantly by using RS. This might provide also additional gain for multiplexing.

2.2.2 RSMA for Multi-Antenna Uplink Communication Systems

Uplink system performance can be improved in terms of connectivity by using Media Access Control (MAC) schemes that use non-orthogonal multiplexing. In multiplexing messages, basic motivation in use of power domain is to increase connectivity. RSMA could also be used for uplink communication, by using SISO Multiple Access Channel [12]. Application of RSMA has different structures and motivations in uplink and downlink communications.

In [20], RSMA is used for uplink in wireless network. They study a case where transmit of superposed messages is done by allocating different levels of power. Received messages are decoded at BS by using SIC. User sum rates are maximized by changing decoding sequence of BS and transmit power of users. They transform maximizing sum-rate problem containing discrete variables of transmit power and decoding to one with a single variable of rate splitting. Each user's optimum power is found for the optimum order of decoding which is calculated through a comprehensive search. It is shown that RSMA provides achieves better results in comparison to NOMA for DoF, and TDMA for sum-rate. Rate splitting and NOMA are used in cooperative communication for uplink [21].

In [22], a centralized and de-centralized relaying protocol is proposed. This study, unlike majority of the work regarding Multiple Input Single Output (MISO) BC related work, involves a phase of channel estimation and relay selection where users send Clear To Send (CTS) packet and a broadcast flag to BS and other users, respectively. This study also considers a generalized case where there are more than two users.

For user co-operations in uplink transmission, RS and NOMA schemes are proposed for transmission and detection that is done in two mini-slots. Each user's own signal is transmitted, and other user's transmitted signal is received at the first slot. By using the protocol of Amplify and Forward, other user's message is relayed by each user with Amplify and Forward protocol. In [23], the authors

calculate source throughput for a random access network by using a protocol of MAC layer with RSMA and Slotted Aloha schemes. RSMA is shown to outperform an OMA-based Slotted Aloha. Thus, they claim that RSMA could be utilized in a random access network to increase connectivity [23].

2.2.3 RSMA for 5G and Beyond

4G and candidate 5G models have some limitations. In these models, performance relies on the accuracy of CSIT. Because of increase in number of antennas and access points of 5G, achieving high accuracy for CSIT is becoming increasingly difficult to meet. In addition, there is sum-rate saturation created by multi-user interference in MISO systems with quantized feedback. 4G and current 5G candidates depend on transmission of private message. A strategy towards handling interference as noise is motivated only in perfect CSIT case. RSMA is proposed as a promising Physical Layer (PHY) strategy for B5G. Majority of arguments supporting RSMA as the promising strategy for B5G revolve around robustness to imperfect CSIT, the RS optimality for achieving the all DoF region of multiuser MISO BC, robust max-min fairness and application oriented results such as Overloaded Systems, Intelligent Reflecting Surface (IRS)-aided Downlink Systems, Ultra-Reliable Low-Latency Communications (URLLC) and enhanced Mobile Broadband (eMBB).

IRSs are re-configurable meta-surfaces intelligently controlled by software. They have passive elements. Each element, after adjusting phases of passive elements, incident electromagnetic wave is reflected independently for each element. Bansal et al [10] consider multiple IRS-assisted downlink MISO. For controlling IRS by using phase shifts, an On-Off scheme is suggested. A formula set for outage probability are driven through using private and common Signal to Interference and Noise Ratio (SINR) data. Suggested system's effectiveness is shown by simulations. Designed system is shown to outperform MU-LP, 1L-RS and 2L-HRS that do not use IRS.

2.2.4 DoF Analysis of RSMA

To improve the performance of communications system significantly, a common viewpoint of is that B5G should use DoF in frequency, user and spatial domains. There has been work on the DoF analysis of RSMA under different network deployments (underloaded and overloaded scenarios) in contrast with MTC and SC-SIC. There has been progress in characterizing over-loaded and under-loaded DoF region for MISO BC under imperfect CSIT. It is shown in [24] that DoF sum obtained by using a linear precoding RS scheme at transmitter and SIC at receiver coincides with theoretical upper-bound on DoF sum for K-user under-loaded MISO BC using CSIT. RS seems to be optimum for achieving DoF sum for K-user under-loaded MISO BC, which is not inline with MTC and SC-SIC that are sub-optimum.

After the studies showing RS to be achieving DoF's all region for K-user MISO BC, RS is adapted to multi-antenna BC [24]. It is shown by [25] that, optimal DoF region for over-loaded MISO BC using heterogeneous CSIT is achieved by using a power allocation scheme having multi-layer.

2.2.5 Rate Splitting Multiple Access for Ultra-Reliable Low-Latency Communications and Enhanced Mobile Broadband

Two of predicted use cases that are envisioned for future generation networks, apart from mMTC are URLLC and eMBB. eMBB requires high spectral efficiency. To provide high reliability, it relies on automatic repeat request re-transmissions. Because of difficult latency constraints, this is not the case with URLLC. Concerning our work focusing on massive MTC, there are studies which use a RS strategy for low-latency downlink communications [26], ultra-reliable

communications [27], Enhanced URLLC and eMBB [28].

In [29], it is shown that RSMA provides reliable connectivity for multiusers under imperfect CSIT. Problem is formulated as lower bound maximization of sum rate, and they try to find power allocation coefficient. To solve this problem, instead of an exhaustive research, they perform an analysis on coefficient of power allocation for time correlation coefficient's asymptotic values in line with the model of Jakes. Their results under varying user speeds show that suggested closed form optimal power allocation coefficient gives similar throughput results with the coefficient found by exhaustive research. The throughput of RSMA is greater than SDMA under the same user speed conditions.

2.2.6 Energy Efficiency of RSMA

Zhou et al [30] address EE-SE trade-off for multi-antenna BC using RSMA scheme. It is shown that RSMA has a potential in improving EE-SE trade-off. EE-SE trade-off issue is a multiple-objective optimization issue with multiple objective functions. Because of complex power consumption and sum rate expressions, each objective function is non-convex. To avoid these difficulties, and obtain a single objective function instead of multiple, they propose weighted-power and weighted-sum approaches. They derive formulae set for a two user system. For a K user system, they use an approximation algorithm for finding optimal precoder. Proposed algorithm with low complexity and computation time is shown to give the same trade-off performance as a sub-optimal convex approximation algorithm for precoding. RSMA provides substantial improvements in Signal Efficiency (SE) and Energy Efficiency (EE) performances in comparison to conventional NOMA and SDMA. [31] similarly studies the SE and EE trade-off. They formulate the issue as non-convex optimization problem with multiple objective functions. They use quadratic constraint. Additionally, they consider a multi-cellular environment. The management of the inter-cellular interference is taken into consideration in [31], [17].

In EE and SE gain analysis, massive MIMO systems are studied with the assumption that there is high quality perfect hardware. Since Radio Frequency (RF) components are costly and circuit power consumption is high, Ahiadormey and Choi [32] study a less costly more realistic system with low-resolution Digital-to-Analog Converter (DAC)s and Analog-to-Digital Converter (ADC)s. They analyze RSMA performance in a massive Multiple Input Multiple Output (MIMO) with less costly DACs and ADCs. They characterize EE and SE, with imperfect Channel State Information (CSI), by studying asymptotic SINRs of respectively private and common messages, respectively. Their simulations verify their analysis. They show that, when less costly DACs and ADCs are used, RS provides better SE than with non-RS.

There are studies [33] - [35] that enhance energy and spectral efficiency by optimizing power allocation. For example, in [33], the authors develop a MDP to model the communication channel. They use proximal policy optimization algorithm to achieve greater average sum rate than Q-learning and Greedy algorithms under different total transmission power and QoS under cost requirements.

Design of SE oriented systems are made with the objective of maximizing SE with constraint of average or peak power. However, this may result in transmitting for a long period of time at maximum allowed power, which in turn it deviates from energy efficiency approach. For the considered power range, increasing the transmit power increases SE at a cost of decreasing EE as shown by [36], [37].

2.3 Age of Information

Instantaneous AoI, a measure of information freshness, is elapsed time at the destination since latest information update's generation time. It differs from conventional metrics like latency and throughput.

$$\Delta(t) = t - U(t) \tag{2.1}$$

where $U(t)$ is newest data packet's generation time, and t is the time. Due to linearity, $\Delta(t)$ shows a saw-tooth type profile. An AoI pattern for RSMA/OMA/NOMA schemes in two-user communication system is given in Figure 2.1.

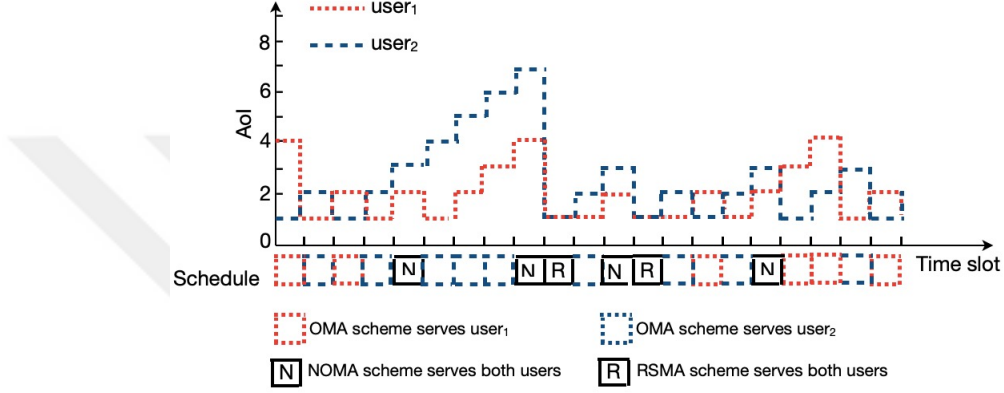


Figure 2.1: AoI schematic of a two-user network with choices of RSMA/OMA/NOMA

It can be observed that, if age difference of users is small, BS can serve rear and far users together, which in turn will reduce AoI for both users. However, if age difference of users is large, BS uses OMA scheme and serves only the user with larger AoI.

Average AoI, $\bar{\Delta}$, is calculated by

$$\bar{\Delta} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \Delta(t) dt \quad (2.2)$$

Maximizing data freshness is an aim of information-update systems. This requires control of packet updates' generation and transmission [38]. [38] provides a policy for information update. There are two common status update models used in the optimization of the AoI: generate-at-will model [38] and randomly generated (arrived) model [39]. In the former model, source node may generate status updates at any time. The latter model with status update generated in accordance with Bernoulli process is studied in [39], where transmission status update is assumed to be error free.

In minimization of average AoI, [40] considers sampling status and process updating designs together. They take also energy constraints of devices into consideration. They suggest an optimal policy for single equipment, a suboptimal policy for multiple ones. The minimization problem of the AoI at a node, with average energy cost constraints, is treated as a MDP having infinite horizon and average cost constraint. By using Lagrangian model, this MDP is transformed to a MDP without constraints. In [11], it is shown that AoI is not the only determining parameter in networked control systems, in particular when there are heterogeneous task requirements and stochastic system dynamics. [15] suggests a distributed transmission policy that is based upon age gain- instantaneous AoI reduction observed after delivery of packets successfully. In case of IoT networks having massive connectivity, centralized scheduling overhead might not be affordable. For aging updates of a wireless network, [41] proposes application-layer and MAC-layer solution, named as Wifresh. WiFresh, designed for Wifi networks, is a scheduling solution dealing with update ageing on internet that is designed for WiFi networks. There are scarce studies, related to AoI, on Markovian source models and channels. Pan et al. [42], consider single source scheduling with choices of Gilbert-Elliott channel and a deterministic channel with lower rate.

2.3.1 Age of Information in Multiple Access Networks

Majority of studies on AoI of networks used to consider status update models only for single-source single-destination cases, e.g. [39], However, recent studies started to focus on more realistic multi-source multi-destination cases, and they in general utilize the OMA technique [43].

In large-scale systems, NOMA scheme, through use of SIC, reduces average AoI, that improves SE substantially in comparison to OMA.

Authors of [44] study an uplink NOMA scheme that combines Multi User Decoding and PHY Network Coding. [45] analyzes NOMA performance in AoI minimization of two node uplink network. It is shown that NOMA and OMA schemes outperform each other under various scenarios. In [46], the objective

is minimization of peak AoI which is achieved through optimization by analyzing allowable bit rate, source entropy, and errors due to channel noise. AoI is minimized through use of an optimal policy to select OMA or NOMA scheme, defined as a MDP issue. To have lower computation complexity by reducing action space in MDP, an action elimination is performed. Optimal policy is verified to be switching type. An approximate average age is obtained through use of a sub-optimal policy, which is based on a Markov chain [47]. Authors in [48] study a status update system for multi-user MIMO. In this system, a group of single-antenna devices sends the latest statuses, through a common channel, to a multiple-antenna access point. According to [5], AoI is one of the trending schemes for energy efficient green NOMA concept for 5G. Authors of [49] propose Lyapunov optimization for solving long term AoI minimization issue through use of NOMA scheme. There are studies in literature, such as [50] - [57], aiming improvement of network's average AoI in a downlink/uplink wireless system. However, all of them exploit NOMA.

2.3.2 Age-Energy Trade-off in Status Update Communication Systems

There are some work that considers age-energy trade-off for improving energy efficiency. A group of studies [58] - [64] approach the problem by the system that wastes energy to the re-transmission of messages on top the energy that is consumed while sensing to construct a packet and transmitting packet.

Another group of studies, [65] - [67], refer to the energy cost instead of energy efficiency. Some studies, [68] - [70], define a joint problem and try to optimize age minimization and energy cost minimization.

Some studies refer to sleep scheduling to decrease the energy consumption [71], [72], while others simply compare the average AoI or peak AoI under different transmit power values [73] - [77].

The literature survey shows that RSMA is a good candidate for B5G in terms

of energy efficiency, AoI, and age-energy trade-off, which are explained in the following chapters.



Chapter 3

System Model

In the literature, there are different adaptive policies used in selecting the policy to be used by the BS. The study made by Wang et al [53] is for selection between OMA and NOMA. In this thesis, the selection is extended to RSMA schemes. This study focuses on RSMA, showing the results in a comparison with RSMA/NOMA/OMA, or NOMA/OMA schemes. For completeness of the thesis and making the reader easily keep track of the theories, not only RSMA but also NOMA/OMA related sections are included in the thesis.

3.1 Multiple Access Methods

In SDMA scheme, based on MU-LP, a user decodes its intended message by handling as noise residual interference from other users. In NOMA, for the users selected by BS, subtracting by SIC, decoding and canceling interference from other users are used properly. RSMA, partially decodes interference and partially handles interference as noise [35]. In OMA, only the user selected by BS is served, and decoding of users do not affect each other. In NOMA, at near user (User1) side, far user (User2)'s signal is subtracted by using SIC technique, and then User1's signal is decoded. At the User2 (far user) side, signal of User1 is treated

as noise and User2's signal is decoded directly [4].

3.1.1 Orthogonal Multiple Access

In OMA scheme, time slots are allocated by BS to transmit to each user separately. When a time slot is planned to transmit to user i , where $i \in \{1, 2\}$, observation at user i is

$$y_i = h_i \sqrt{P} m_i + n_i \quad (3.1)$$

P ; BS's power in transmission, which is assumed to be constant, h_i is channel coefficient between user i and BS, and m_i is status information for user i . $h_i = \sqrt{d_i^{-\tau}} g_i$, where $d_i = c_i/c_0$ is the normalized distance, c_i and c_0 distances from BS to user i and reference distance. τ is path loss distribution and $g_i \sim \mathcal{CN}(0, 1)$. ($\mathcal{CN}$; normal distribution). n_i is noise with variance σ_i^2 . It is assumed that $d_1 < d_2$, then, $\mathbb{E}[|h_2|^2] < \mathbb{E}[|h_1|^2]$, which is assumed to be identical to simplify the analysis. When a signal is received, the message could be decoded with a SNR ($\gamma_i = |h_i|^2 \rho$), $\rho = P/\sigma^2$ is SNR in transmission. User i 's rate is defined by $R_i^{\text{OMA}} = \log(1 + \gamma_i)$. For OMA scheme used, outage probability of user i is calculated as

$$P_i^{\text{OMA}} = 1 - P(R_i^{\text{OMA}} \geq R_i) = 1 - \exp\left(-\frac{(2^{R_i} - 1)d_i^\tau}{\rho}\right) \quad (3.2)$$

R_i is user i 's target rate. To simplify the analysis, both users' target rates are assumed to be identical [53].

3.1.2 Nonorthogonal Multiple Access

In NOMA scheme, signals to be sent to different users are combined in power domain through allocation of different power levels to each user. By using SIC, two users can recover their information successfully within the same time slot. Observation at user i is calculated as

$$y_i = h_i(\sqrt{\alpha_1 P} m_1 + \sqrt{\alpha_2 P} m_2) + n_i, \quad (3.3)$$

where α_i is coefficient for power allocation, and $\alpha_1 + \alpha_2 = 1$. Since it is expected that BS allocates larger power to far user, $\alpha_2 > \alpha_1$ without loss of generality. User 2 directly decodes its message through handling m_1 as interference. User 2's received SINR is calculated by

$$\gamma_{22} = \alpha_2 |h_2|^2 / (\alpha_1 |h_2|^2 + 1/\rho). \quad (3.4)$$

User 2's outage probability can be calculated by

$$\begin{aligned} P_2^{NOMA} &= 1 - P(\log(1 + \gamma_{22}) \geq R) \\ &= 1 - \exp\left(-\frac{(2^R - 1)d_2^\tau}{\rho(\alpha_2 - \alpha_1(2^R - 1))}\right), \end{aligned} \quad (3.5)$$

Since $\alpha_2 - \alpha_1(2^R - 1)$ should be positive, $\alpha_2 > \frac{2^R - 1}{2^R}$ is enforced. For user 1, closer to BS, it conducts SIC. Similar to what user 2 has done, user 1 will decode m_2 through handling m_1 as interference. SINR received by user 1 while decoding m_2 , γ_{12} , is calculated by

$$\gamma_{12} = \alpha_2 |h_1|^2 / (\alpha_1 |h_1|^2 + 1/\rho). \quad (3.6)$$

SINR can be expresses as

$$\gamma_{11} = \alpha_1 |h_1|^2 \rho \quad (3.7)$$

User 1's outage probability is given by

$$\begin{aligned} P_1^{NOMA} &= 1 - P(\log(1 + \gamma_{12}) \geq R \& \log(1 + \gamma_{11}) \geq R) \\ &= 1 - \exp\left(-\max\left\{\frac{(2^R - 1)d_1^\tau}{\rho(\alpha_2 - \alpha_1(2^R - 1))}, \frac{(2^R - 1)d_1^\tau}{\alpha_1 \rho}\right\}\right), \end{aligned} \quad (3.8)$$

Comparison of outage probabilities for OMA and NOMA, it can concluded that NOMA demands transmission to both users, but this may increase outage probability of the user in worse conditions. By power allocation for each user, outage probability for NOMA is determined. While using NOMA, BS allocates appropriate powers to each user. In this thesis, power levels for allocating to users are assumed to be discrete. Power level for allocating to user i , shown as $\alpha_i P$, where α_i might be any value of $\{0, \frac{1}{N}, \frac{2}{N}, \frac{3}{N}, \dots, 1\}$. $P_1 + P_2 = P$ and then $\alpha_1 = 1 - \alpha_2$. Since user 2 is assumed to be the far user, ($d_1 < d_2$ and $c_1 < c_2$), $\alpha_2 > \alpha_1$, and thus

$\alpha_2 > 0.5$. Substituting this into $\alpha_2 > \frac{2^R-1}{2^R}$, it can be concluded that α_2 should take any value of $\{0, \max\{\frac{1}{2} + \frac{1}{N}, \lceil \frac{(2^R-1)N}{2^R} \rceil \frac{1}{N}\}, \max\{\frac{1}{2} + \frac{1}{N}, \lceil \frac{(2^R-1)N}{2^R} \rceil \frac{1}{N}\} + \frac{1}{N}, \dots, 1\}$.

$\alpha_2(t)$ shows fraction of power to be allocated to user 2. In a policy where OMA and NOMA are the available scheme, for limit values of α_i , $\alpha_2(t) = 1$ and $\alpha_2(t) = 0$, BS will select OMA, transmit respectively only to user 2 and user 1. For other values of α_i , BS will select NOMA, so that it will serve both users simultaneously. Then, $\alpha_2(t)P$ is the power level for allocating to user 2. Thus remaining power $(1 - \alpha_2(t))P$ is for user 1.

It is assumed that π is policy be used by BS in transmitting, with the action set for the time slot, denoted as $\{a_t\}$. $\{a_t\} \in \{0, \max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R-1)N}{2^R} \rceil\}, \dots, N\}$ shows that BS's $a_t P/N$ power fraction is used for user 2. BS selects OMA, when $a_t = 0$, and makes transmission to user 1. When $a_t = N$, BS selects OMA, and makes transmission to only user 2. For other values of α , BS will select NOMA, so that it will serve both users simultaneously. $a_t P/N$ is the power level for allocating to user 2. $P - a_t P/N$ is for allocating to user 1 [53].

3.1.3 Rate Splitting Multiple Access

RSMA is versatile, and can be applied to various users and network load levels since it can easily switch to different schemes, such as SDMA and NOMA [4]. For network load (overload and underload), CSIT accuracy, and user deployments (strength of channel strength, direction of channel), RSMA is superior to NOMA. RSMA in general provides a rate better than NOMA for the same conditions.

In a K user case, in this thesis $K = 2$, message of user i , W_i , is split as private and common parts, $W_{p,i}$, $W_{c,i}$, $\forall i \in K$. $W_{c,i}$, $\forall i \in K$, are combined as W_c . W_c and $W_{p,i}$, $\forall i \in K$ are encoded respectively as streams s_c , s_i , $\forall i \in K$. All streams are subjected to linear precoding. m_i and m_c are respectively private and common status update information. α_c is common power allocation factor indicating ratio of common message power to total transmit power, and α_i private power allocation factor indicating ratio of power for private message for

user i to total power for all private messages. In this context, in RSMA mode, BS allocates $P\alpha_c$ amount of power to common status update information and $(1 - \alpha_c)P\alpha_i$ amount of power to private status update information for user i , and $\sum_{i=1}^{K=2} \alpha_i = 1$. Observation at user i is expressed by

$$y_i = h_i(\sqrt{\alpha_c P} m_c + \sum_{i=1}^{K=2} \sqrt{(1 - \alpha_c) P \alpha_i} m_i) \quad (3.9)$$

Specifically, when $\alpha_c = 0$, BS selects OMA or SDMA depending on the value of α_i . When $\alpha_i = 0$ or $\alpha_i = 1$, if $\alpha_i = 1$ and $\alpha_k = 0, k \neq i, \forall k \in K$, BS selects OMA, if not BS selects SDMA. When $\alpha_c \neq 0$, BS selects RSMA or NOMA depending on the value of α_i . When $\alpha_c \neq 0$, if $\alpha_i = 1$ and $\alpha_k = 0, k \neq i, \forall k \in K$, BS selects NOMA, if not it selects RSMA. If no power is allocated to one of user's messages, in NOMA mode, that message can be interpreted as m_c in Equation 3.9. The outage probabilities are derived for each mode and for analysis, Equations 3.1, 3.3, 3.9 are considered for OMA, NOMA and RSMA respectively. m_c is decoded by both users through handling interference from private messages $m_i, \forall i \in K$ as noise. SINR to decode m_c at user $i, \forall i \in K$ is

$$\gamma_{c,i} = \frac{\alpha_c |h_i|^2}{((1 - \alpha_c) |h_i|^2 + 1/\rho)}. \quad (3.10)$$

After decoding m_c and subtracting from received signal through SIC, user i 's private message m_i is decoded through handling user j 's ($j \neq i$) interference as noise. SINR to decode m_i for user $i, \forall i \in K$ is

$$\gamma_{p,i} = \frac{(1 - \alpha_c) \alpha_i |h_i|^2}{((1 - \alpha_c) \sum_{j=1, j \neq i}^{K=2} \alpha_j |h_i|^2 + 1/\rho)}. \quad (3.11)$$

There are different analytical expressions to indicate the outage probability for rate-splitting multiple access. One option, similar to (3.8) would be the following:

Option 1.

$$P_i^{\text{RSMA}} = 1 - P(\log(1 + \gamma_{p,i}) \geq R \quad \& \quad \Theta_{c,i} \min_{\forall i \in K} \log(1 + \gamma_{c,i}) \geq R) \quad (3.12)$$

Denote R_c as the common rate. For warranting decode of common message for all users, R_c should not be allowed to be above $\min_{\forall i \in K} R_{c,i} = \min_{\forall i \in K} \log(1 + \gamma_{c,i})$. As R_c is common to K users, and C_i belongs to i^{th} user. $\Theta_{c,i}$ indicates ratio of C_i over common rate, R_c , where $\Theta_{c,i} R_c = C_i$ and $\sum_{i \in K} C_i = R_c$.

This expression of outage probability for RSMA in (3.12) ignores the i^{th} user's target rates for private and common messages. According to [78], decreasing outage probability of each user requires giving equal importance to properly decode of both messages. Therefore, we prefer Option 2 and use the outage probability expressions inspired by [19], [78].

Option 2.

Target rates, common target rates, and private target rates; $\{R_i^* = R_i^{(c)*} + R_i^{(p)*}\}_{i \in K}$, $\{R_i^{(c)*}\}_{i \in K}$, $\{R_i^{(p)*}\}_{i \in K}$. $R_i^{(c)*} = R_i^* \lambda_{c,i}$ and $R_i^{(p)*} = R_i^* (1 - \lambda_{c,i})$. Decoding of privates messages can be done after successful decoding of common messages. When one the following occurs, there will be outage of i :

- User i is not successful in decoding common part, $R_i^{(c)*} \leq \sum_{j \in K} R_j^{(c)*}$;
- User i is successful in decoding common part, however not successful for private part, $R_i^{(c)*} \geq \sum_{j \in K} R_j^{(c)*}$ and $R_i^{(p)*} \leq R_i^{(p)*}$

So user i 's outage probability is

$$\begin{aligned}
P_i^{\text{RSMA}} &= P\left((R_{c,i} \geq \sum_{j \in K} R_j^{(c)*}) \cap (R_{p,i} \leq R_i^{(p)*})\right) + P\left(R_{c,i} \leq \sum_{j \in K} R_j^{(c)*}\right) \\
&= P\left(\left(\log(1 + \gamma_{c,i}) \geq \sum_{j \in K} R_j^{(c)*} \cap (\log(1 + \gamma_{p,i}) \leq R_i^{(p)*})\right)\right) \\
&\quad + P\left(\log(1 + \gamma_{c,i}) \leq \sum_{j \in K} R_j^{(c)*}\right) \\
&= P\left(\left(\frac{|h_i|^2 + 1/\rho}{((1 - \alpha_c)|h_i|^2 + 1/\rho)} \geq \sum_{j \in K} R_j^{(c)*}\right)\right. \\
&\quad \left. \cap \left(\frac{(1 - \alpha_c)|h_i|^2}{((1 - \alpha_c) \sum_{j=1, j \neq i}^K \alpha_j |h_i|^2 + 1/\rho)} \leq R_i^{(p)*}\right)\right) \\
&\quad + P\left(\frac{|h_i|^2 + 1/\rho}{((1 - \alpha_c)|h_i|^2 + 1/\rho)} \leq \sum_{j \in K} R_j^{(c)*}\right)
\end{aligned} \tag{3.13}$$

Let's replace $|h_i|^2$ with a , $1/\rho$ with b , $\sum_{j \in K} R_j^{(c)*}$ with c and $R_i^{(p)*}$ with d for

simplicity.

$$\begin{aligned}
P_i^{\text{RSMA}} &= P\left(\left(\frac{a+b}{a(1-\alpha_c)+b} \geq 2^c\right) \cap \left(\frac{a(1-\alpha_c)+b}{a(1-\alpha_c) \sum_{j=1, j \neq i}^K \alpha_j + b} \leq 2^d\right)\right) \\
&\quad + P\left(\frac{a+b}{a(1-\alpha_c)+b} \leq 2^c\right) \\
&= P\left(\frac{2^c b - b}{1 - 2^c(1-\alpha_c)} \leq a \leq \frac{2^d b - b}{1 - \alpha_c 2^d(1-\alpha_c) \sum_{j=1, j \neq i}^K \alpha_j}\right) \\
&\quad + P\left(a \leq \frac{2^c b - b}{1 - 2^c(1-\alpha_c)}\right)
\end{aligned} \tag{3.14}$$

a was replaced with $|h_i|^2$ where $h_i = \sqrt{d_i^{-\tau}} g_i$ and $g_i \sim \mathcal{CN}(0, 1)$. Hence, $|h_i|^2 = d_i^{-\tau} |g_i|^2$ where $|g_i|^2 \sim \text{Exp}(1)$. Overall $|h_i|^2 \sim \text{Exp}(d_i^\tau)$. If we rewrite (3.14) in terms of the cumulative distribution function,

$$\begin{aligned}
P_i^{\text{RSMA}} &= P\left(a \leq \frac{2^d b - b}{1 - \alpha_c - 2^d(1-\alpha_c) \sum_{j=1, j \neq i}^{K=2} \alpha_j}\right) \\
&= F\left(\frac{2^d b - b}{1 - \alpha_c - 2^d(1-\alpha_c) \sum_{j=1, j \neq i}^{K=2} \alpha_j}\right)
\end{aligned} \tag{3.15}$$

Warranting common message's decoding failure will yield to failure of private message, Proposition 2 in [19] should be satisfied. $\lambda_{c,i}$, α_i and α_c should be selected in a way it satisfies;

$$\frac{2^c b - b}{1 - 2^c(1-\alpha_c)} \leq \frac{2^d b - b}{1 - \alpha_c - 2^d(1-\alpha_c) \sum_{j=1, j \neq i}^{K=2} \alpha_j} \tag{3.16}$$

3.2 Age of Information Analysis

Freshness of information received by user is evaluated by AoI, which is a performance metric. AoI is elapsed time from last message's generation till current time [6]. In this thesis, we use generate-at-will model and consider slot duration normalized to unity. When a user, in the considered time slot, receives its packet, AoI of this user will be made equal to 1, otherwise be increased by 1.

$\Delta_i(t)$ is calculated as

$$\Delta_i(t+1) = \begin{cases} 1 & v_i(t) = 1 \\ \Delta_i(t) + 1 & v_i(t) = 0 \end{cases} \tag{3.17}$$

The indicator $v_i(t)$ is set to 1 if the user successfully receives information, otherwise $v_i(t)$ is set to 0. WSAoI of two users is used as a measure for timeliness of the communication system. WSAoI ($\bar{\Delta}$) is defined as

$$\bar{\Delta} = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \left[\sum_{i=1}^2 \sum_{t=1}^T w_i \Delta_i(t) \right] \quad (3.18)$$

w_i is user i 's weight, for two users, $\sum_{i=1}^2 w_i = 1$, and $\Delta_i(t)$ is user i 's AoI at time slot t . Time symbol in age will be omitted for brevity. In the two user scenario used in this thesis, Δ_1 and Δ_2 stand for AoI of user 1 and user 2, respectively. Difference of expected current and next state's weighted summed ages is AoI drop expected, denoted by $\mathbb{E}[\eta(s, a_t)]$.

For RSMA, we should add a new term, α_c , in a_t . From now on, $a_t = \{\alpha_t, \alpha_c\}$ where $\alpha_t \in \{0, 1, 2, 3, \dots, N\}$ satisfy (3.16) for RSMA, $\{max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R - 1)N}{2^R} \rceil\}, \dots\}$ for NOMA and $\{0, N\}$ for OMA. NOMA and OMA is not a function of α_c , however, the condition that $\alpha_c = 0$ implies that no power is allocated to common message, and such a message that does not exist in NOMA and OMA. Therefore, we associate the $\alpha_c = 0$ condition with NOMA and OMA schemes. For NOMA and OMA, $a_t = \{\alpha_t, 0\}$ and α_t can be used interchangeably. Relation between AoI and outage probability is given in terms of transition probabilities as a function of α_c and α_2 for user i 's given target rate, shown as R_i , and ratio of user i 's common target rate over user i 's target rate, shown as $\lambda_{c,i}$. It is highlighted that the set of possible values for α_2 may vary between RSMA and OMA, NOMA, as shown in the following equation sets, respectively.

$$P((1, \Delta_2 + 1) | (\Delta_1, \Delta_2), a_t = \{0, 0\}) = 1 - P_1^{\text{OMA}} \quad (3.19)$$

$$P((\Delta_1 + 1, \Delta_2 + 1) | (\Delta_1, \Delta_2), a_t = \{0, 0\}) = P_1^{\text{OMA}} \quad (3.20)$$

$$P((\Delta_1 + 1, 1) | (\Delta_1, \Delta_2), a_t = \{N, 0\}) = 1 - P_2^{\text{OMA}} \quad (3.21)$$

$$P((\Delta_1 + 1, \Delta_2 + 1) | (\Delta_1, \Delta_2), a_t = \{N, 0\}) = P_2^{\text{OMA}} \quad (3.22)$$

and if $\alpha_c \in (0, 1]$, $\alpha_t \in \{0, 1, 2, 3, \dots, N\}$, and $\lambda_{c,i}$ satisfy (3.16)

$$\begin{aligned} P((1, \Delta_2 + 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, \alpha_c\}, \lambda_{c,1}, \lambda_{c,2}) \\ = (1 - P_1^{\text{RSMA}}(a_t)) P_2^{\text{RSMA}}(a_t) \end{aligned} \quad (3.23)$$

$$\begin{aligned} P((\Delta_1 + 1, 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, \alpha_c\}, \lambda_{c,1}, \lambda_{c,2}) \\ = (1 - P_2^{\text{RSMA}}(a_t)) P_1^{\text{RSMA}}(a_t) \end{aligned} \quad (3.24)$$

$$\begin{aligned} P((1, 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, \alpha_c\}, \lambda_{c,1}, \lambda_{c,2}) \\ = (1 - P_2^{\text{RSMA}}(a_t)) (1 - P_1^{\text{RSMA}}(a_t)) \end{aligned} \quad (3.25)$$

$$\begin{aligned} P((\Delta_1 + 1, \Delta_2 + 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, \alpha_c\}, \lambda_{c,1}, \lambda_{c,2}) = P_1^{\text{RSMA}}(a_t) \\ P_2^{\text{RSMA}}(a_t) \end{aligned} \quad (3.26)$$

When α_t is not equal to 0 or N , and $\alpha_c = 0$

$$P((1, \Delta_2 + 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, 0\}) = (1 - P_1^{\text{NOMA}}(a_t)) P_2^{\text{NOMA}}(a_t) \quad (3.27)$$

$$P((\Delta_1 + 1, 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, 0\}) = (1 - P_2^{\text{NOMA}}(a_t)) P_1^{\text{NOMA}}(a_t) \quad (3.28)$$

$$P((1, 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, 0\}) = (1 - P_2^{\text{NOMA}}(a_t)) (1 - P_1^{\text{NOMA}}(a_t)) \quad (3.29)$$

$$P((\Delta_1 + 1, \Delta_2 + 1)|(\Delta_1, \Delta_2), a_t = \{\alpha_t, 0\}) = P_1^{\text{NOMA}}(a_t) P_2^{\text{NOMA}}(a_t) \quad (3.30)$$

where P_1^{NOMA} , P_2^{NOMA} , P_1^{RSMA} and P_2^{RSMA} are user 1's and user 2's outage probabilities, respectively, using NOMA, and RSMA with $\alpha_2 = \alpha_t/N$ and $\alpha_1 + \alpha_2 = 1$.

3.3 Problem Definition

We study a downlink transmission in a wireless network. We assume that transmission of BS to multiple users is conducted in time slots. For simplicity, a case with two users is investigated throughout the thesis. It is also assumed that fresh information for both users could be generated at each time slot's beginning. In the literature, this is named as *generate-at-will* model. Model assumes that status updates can be generated by the source node at any time. This model is practical since most BSs have the ability for controlling time of data downloading

Table 3.1: Assumptions and constraints of Problem 1

Assumptions	- BS can transmit timely to the users in time slots. - Fresh information for each user could be generated at each time slot's beginning. - User 2 is farther to BS than user 1. - BS could switch between RSMA, OMA and NOMA. - BS can allocate power dynamically to the users according to the network status. - When a user gets its packet, it sends ACK to BS. - ACK link is delay and error free.
Constraints	- For simplicity, a two-user scenario is investigated. - Downlink transmission is studied.

through the server or cloud. It is assumed that, for the downlink transmission, BS could adaptively switch between RSMA, so that in a time slot both users can receive their packets at the same time. It is also assumed that power can be allocated dynamically to the users by BS. User i sends Acknowledgement (ACK) after receipt of message. ACK link is assumed to be delay and error free.

Design objective of this study is to define an optimal and practical suboptimal policy to minimize WSAoI of the network. With the assumptions and constraints given in Table 3.1, problem could be expressed by

Problem 1.

$$\min_{\pi} \bar{\Delta}. \quad (3.31)$$

π is optimal/sub-optimal policy, and $\bar{\Delta}$ is average WSAoI to be minimized. After the minimization process, the trade-off between WSAoI and energy is also studied in Chapter 5.

The optimal policy and the practical policy that will use a scheme in selection between RSMA/OMA/NOMA are based on a power allocation policy. The policy to be used is explained in Chapter 4.

Chapter 4

Power Allocation Policy for Rate Splitting Multiple Access

BS should make a power allocation and scheme decision at a time slot to send messages to their intended users. There are multiple schemes, such as OMA, NOMA and RSMA to transmit the users their messages. The power allocation can be expressed in terms of the values of common and private power allocation factors assigned by BS. Values of the power allocation factors express which users to serve and if any power is allocated to the common message. Therefore, the values of the power allocation factors indicate a scheme decision by implying BS how many users to serve and whether to split the messages into common and private parts and merge the common parts into a common message. The problem is a minimization problem, that is to minimize WSAoI of the network by power allocation. We associate the increase of AoI of user with the event of failure in decoding its message. The transition probabilities are expressed in terms of outage probabilities are explained in the Chapter 3.

The policies for NOMA/OMA schemes are established by Wang et al [53]. We expand these policies to include also RSMA selection. Since the main focus in this thesis is use of RSMA, power allocation policy is explained in detail separately in this chapter. The age optimal/sub-optimal policies are explained in the following

sections.

4.1 Age Optimal Policy

Design of scheduling policy is a dynamic decision-making issue. We approach the minimization of WSAoI, defined as Problem 1 from a time slotted manner. We associate the possible AoI of users in the next time slot with the outage probabilities, which are the functions of power allocation factor values. We discretize the values of power allocation factors and define action spaces in Chapter 3. Here, we introduce a MDP with a motivation to minimize WSAoI with an age-aware policy. We show that an optimal policy exists. Reduction of action space is discussed and a suboptimal policy including RSMA is proposed.

4.1.1 Formulation of MDP

MDP problem is defined as a tuple $\{S, A, P, r\}$, where

- State space $S = \mathbb{Z}^+ \times \mathbb{Z}^+$: Time is split into slots. In time slot t , user i has AoI indicated as $\Delta_{i,t}$. State at time t , shown as s_t , is expressed as $\triangleq (\Delta_{1,t}, \Delta_{2,t})$.
- Action space for NOMA and OMA $A_{\text{OMA}, \text{NOMA}} = \{0, \max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R - 1)N}{2^R} \rceil\}, \dots, N\} \times \{\alpha_c = 0\}$: The transmission policy for OMA and NOMA depends on α or for two-user case, simply α_2 for NOMA and OMA transmission modes.
- Action space for RSMA $A_{\text{RSMA}} \subseteq \{0, 1, 2, 3, \dots, N\} \times \{\alpha_c\}$ such that all elements of A_{RSMA} satisfy (3.16): The transmission policy for RSMA mode depends on α_c and α_2 .
- Transition probability P , $P(s_t + 1 | s_t, a_t)$, is for transition from s_t to s_{t+1} with action a_t where $a_t \in A_{\text{OMA}, \text{NOMA}} \cup A_{\text{RSMA}}$. We have the transition

probabilities expressed in (3.19)-(3.30), in terms of users' outage probabilities, when they receive status updates in either RSMA, NOMA or OMA.

- $r : S \times A \rightarrow \mathbb{R}$ is reward, defined in terms state and action pairs by $r(s_t, a_t) = w(s_t) = w_1 \Delta_{1,t} + w_2 \Delta_{2,t}$.

Assume that π shows the transmission policy for BS. Policy contains a set of decision rules as $\pi = (\pi_1, \dots)$. As it is history and time independent, it is stationary and $\pi_t = \pi_t(a_t | s_t)$. With an initial state s_0 , choosing action a_t with a probability of $\pi_t(a_t | s_t)$, horizon average cost is calculated by

$$C(\pi, s_0) = \lim_{T \rightarrow \infty} \sup \frac{1}{T} \sum_{k=0}^T \mathbb{E}_{s_0}^{\pi} [r(s_k, a_k) | s_0] \quad (4.1)$$

Problem 1 could be transferred into a MDP problem as follows,

Problem 2.

$$\min_{\pi} C(\pi, s_0). \quad (4.2)$$

where π is optimal policy, C is the average cost to be minimized. A stationary and deterministic optimal policy for Problem 2 exists based on:

Theorem 1. *There is a constant I^* , a bounded function $f(\Delta_1, \Delta_2) : S \rightarrow \mathbb{R}$, a deterministic and stationary optimal policy π^* , satisfying equation of average cost optimality,*

$$I^* + f(\Delta_1, \Delta_2) = \min_{a_t \in A} (w_1 \Delta_{1,t} + w_2 \Delta_{2,t} + \mathbb{E}[f(\hat{\Delta}_1, \hat{\Delta}_2)]) \quad (4.3)$$

where I^* is (Δ_1, Δ_2) taking action a_t .

Theorem 1 assumes that optimal policy does not depend on time. It is based on the state, and deterministically selects an action. The proof is given in Appendix A.

4.1.2 Action Elimination

Here, we refer to the abstraction technique to eliminate under-performing actions in the action space, which results in a reduced action space. According to (3.5)

and (3.8), outage probability of user 2 served in NOMA, P_2^{NOMA} , decreases with α_2 ; $P_2^{\text{NOMA}}(a_t)$ is decreasing in action a_t when $\max\left\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R-1)N}{2^R} \rceil\right\} < a_t < N$. On the other hand, since $\alpha_1 + \alpha_2 = 1$, user 1's outage probability, served in NOMA (P_1^{NOMA}) decreases with α_2 if $\frac{2^R}{2^R+1} > \alpha_2 > \frac{2^R-1}{2^R}$, increases with α_2 if $1 > \alpha_2 > \frac{2^R}{2^R+1}$. Thus, $P_1^{\text{NOMA}}(a_t)$ decreases with a_t if $a_t \in \{\max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R-1)N}{2^R} \rceil\}, \dots, \lfloor \frac{2^R N}{2^R+1} \rfloor\}$, increases with a_t if $a_t \in \{\lceil \frac{2^R N}{2^R+1} \rceil, \lceil \frac{2^R N}{2^R+1} \rceil + 1, \dots, N-1\}$. Corner action, that is $a_t = \lfloor \frac{2^R N}{2^R+1} \rfloor$ would be selected over $a_t \in \{\max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R-1)N}{2^R} \rceil\}, \max\{\lceil \frac{N}{2} \rceil + 1, \lceil \frac{(2^R-1)N}{2^R} \rceil\} + 1, \dots, \lfloor \frac{2^R N}{2^R+1} \rfloor\}$ when the decision aims to reduce AoI of both users because it results in a lower outage probability when compared. Therefore, it is possible to reduce action space to $a_t \in \{0, \lfloor \frac{2^R N}{2^R+1} \rfloor, \lfloor \frac{2^R N}{2^R+1} \rfloor + 1, \dots, N\}$ [53].

With action elimination, the exhaustive search among the finite action space is restricted without losing an action from the optimal policy. Thus, there is no penalty due to action elimination.

4.1.3 Structural Results in Optimal Policy

Based on behaviour of outage probability, we refer to an optimal policy structure, with the aim of obtaining boundaries of reduced action space.

Theorem 2. π^* , optimal policy, is switching type. If a, b are arbitrary actions of set $\{0, \lfloor \frac{2^R N}{2^R+1} \rfloor, \lfloor \frac{2^R N}{2^R+1} \rfloor + 1, \dots, N\}$,

- If $\pi^*((\Delta_1, \Delta_2)) = a$, $\pi^*((\Delta_1, \Delta_2 + n)) = b$, $b \geq a$,
- If $\pi^*((\Delta_1, \Delta_2)) = a$, $\pi^*((\Delta_1 + n, \Delta_2)) = b$, $b \leq a$ [53],

where n ; a positive integer.

Proof is given in Appendix B.

By using this structure, it is possible to develop an algorithm for value iteration as in [39, Algorithm 1] for reducing optimal policy calculation complexity.

4.2 Suboptimal Policy

According to the optimal policy, at a time slot, the process can be iterated for the upcoming future slots, while computing WSAoI for the future potential states up to a horizon, ideally at infinity. The horizon average cost would converge due to the sum expression of the expectation of the rewards. Looking back from the converged slot back at the actions taken, the policy would be obtained. According to the optimal policy obtained, the action that BS should take in the current state in the considered time slot is obtained. In the next time slot, if all the conditions remain the same i.e target rates, the results from the considered slot would apply. Unless the conditions remain the same, the approach is repeated. We will propose a sub-optimal policy extended to RSMA.

Using the idea of Max-weight policy [41], sub-optimal policy to be proposed uses transition probability in MDP maximizing only WSAoI drop in a time slot, the difference between current and possible next state's WSAoI. By using (3.31), value of expected AoI drop, shown as $\mathbb{E}[\beta(s, a_t)]$, is calculated by

$$\mathbb{E}[\beta(s, a_t)] = \begin{cases} w_1(1 - P_1^{\text{OMA}})\Delta_1 - 1 & \alpha_2 = 0, \alpha_c = 0 \\ w_2(1 - P_2^{\text{OMA}})\Delta_2 - 1 & \alpha_2 = 1, \alpha_c = 0 \\ w_1(1 - P_1^{\text{NOMA}}(a_t))\Delta_1 + w_2(1 - P_2^{\text{NOMA}}(a_t))\Delta_2 - 1 & \alpha_2 \in \{\alpha_t/N\}, \alpha_2 \neq \{0, 1\}, \alpha_c = 0 \\ w_1(1 - P_1^{\text{RSMA}}(a_t))\Delta_1 + w_2(1 - P_2^{\text{RSMA}}(a_t))\Delta_2 - 1 & \alpha_2 \in \{\alpha_t/N\}, \alpha_c \in (0, 1] \end{cases} \quad (4.4)$$

Sub-optimal policy $\bar{\pi}$'s action at state s :

$$\bar{\pi}(s) = \arg \max_{\pi} \mathbb{E}[\beta(s, a_t)]. \quad (4.5)$$

According to [47, 53], near optimal performance is achievable with sub-optimal policy. Implementation of sub-optimal policy is easy, with lookup tables and a search method. The sub-optimal policy in comparison to optimal, does not require iterations, based on Relative Value Iteration method [39, Algorithm 1] to

calculate optimal policy. In optimal MDP policy, both action and state spaces enlarge exponentially as users number and resolution increase. MDP method would suffer from high complexity due to the discrete state space with large cardinality. The suboptimal policy investigated in this two-user scenario with a BS serving could be extended to the general case in a slotted manner with multiple users. Please refer to [79], for a multi-cell network serving multiple users and the associated SINR expressions for each user's private and common messages.

Suboptimal policy for OMA/NOMA has been studied by many researchers, however, combining age-aware power allocation policy/suboptimal policy with RSMA, to our knowledge, is the first study in literature, is studied in this thesis.

Chapter 5

Numerical Results

In this chapter, scenarios, performance metrics, and comparisons made, are explained by using the results of a series of simulations. The simulations are for a BS downlink communications with two-user scenario with user 1 (near user) is closer to the BS than user 2 (far user).

The performance metrics are WSAoI minimization, and age-energy trade-off. Results of the proposed age-aware optimal, and suboptimal policy are shown as results of parametric studies, where effect of each parameter on the performance metrics is studied by changing values of the parameter while keeping others constant.

5.1 Introduction

Results of simulations of two-user scenarios for evaluating the proposed RSMA/OMA/NOMA scheme's effectiveness are given in this chapter. State space for infinite horizon is approximated as countable finite states ($\Delta_i \leq 100, \forall i$). User target rates are R_1^* and R_2^* . User weights are w_1 and w_2 . User 1 is assumed to be at closer distance to BS than user 2. We assume that path loss exponent is 2. A condition to stop the simulations is $(s_1, s_2) = (1, 1)$.

The research model is based on WSAoI minimization. Since the adaptive policy uses power rates in the decision process, WSAoI minimization contributes also to energy efficient green activity management together with use of action elimination and suboptimal policy. In this thesis, the studies are mostly done for proposed adaptive policy RSMA/OMA/NOMA with two-user scenarios. NOMA/OMA or NOMA only or OMA only scenarios are studied in this thesis for selected scenarios, since the adaptive policy proposed in this thesis makes a selection, at any time, among RSMA/NOMA/OMA with an age-aware green approach, in turn results in better performance metrics than NOMA/OMA or OMA only or OMA only schemes as shown in the age-energy tradeoff graphics.

There are five parameters affecting WSAoI minimization: user target rate, common target rate, user weight distribution, distance of user to BS, transmission SNR. In the parametric analyses, for each case, values for the parameter to be analysed are changed, while values of all the other parameters are kept constant, to see parameter's effect on performance metric, WSAoI. In age-energy tradeoff analysis, the age (WSAoI) is calculated for all discrete power levels (transmission SNRs) for the selected user distance cases while keeping all the other parameters (user rate and user weight distributions) constant. Simulations are done under the scenarios that analyse effect of changing only one parameter's value of a selected parameter while keeping the values of all the other parameters constant. Considering that there are five parameters to be analysed and at each case only one parameter's value is changed, and each parameter to be analysed can take a set of different values, there are vast number of analyses due to the various combinations of the available parameters. Numerical results of the simulations that analyze the effects of the parameters are given in the following sections/subsections.

The conditions and results of parametric analysis are given in the following sections as tables, 2-D plots for age-energy tradeoff analysis and colored 2-D graphics for optimal policy analysis. The colored 2-D graphics, an example of which is given in Figure 5.1(a), show RSMA/NOMA/OMA selection scheme results for two-user scenarios defined in the tables of the related parametric analysis. AoI for user 1 (Δ_1) and user 2 (Δ_2) are shown in 100 scale in the horizontal and vertical axes, respectively. Each point in the 2-D graph represents an action for

a state $s = (\Delta_1, \Delta_2)$. For the example case shown in Figure 5.1(a), $a_t = 10$ is shown as purple (OMA, user 2), $a_t = 8$ as blue (NOMA, both users), $a_t = 7$ as green (NOMA, for both users), $a_t = 9$ as orange (NOMA, both users), $a_t = 0$ as yellow area (OMA, user 1), where $N = 10$ and $A = \{0, 6, 7, 8, 9, 10\}$. The results of the simulation of optimal policy model are the decisions for selection of RSMA/NOMA/OMA at all actions of a given case, and are shown in a 2-D graph by representing each selection, i.e. an action for a state $s = (\Delta_1, \Delta_2)$, as a different colored point.

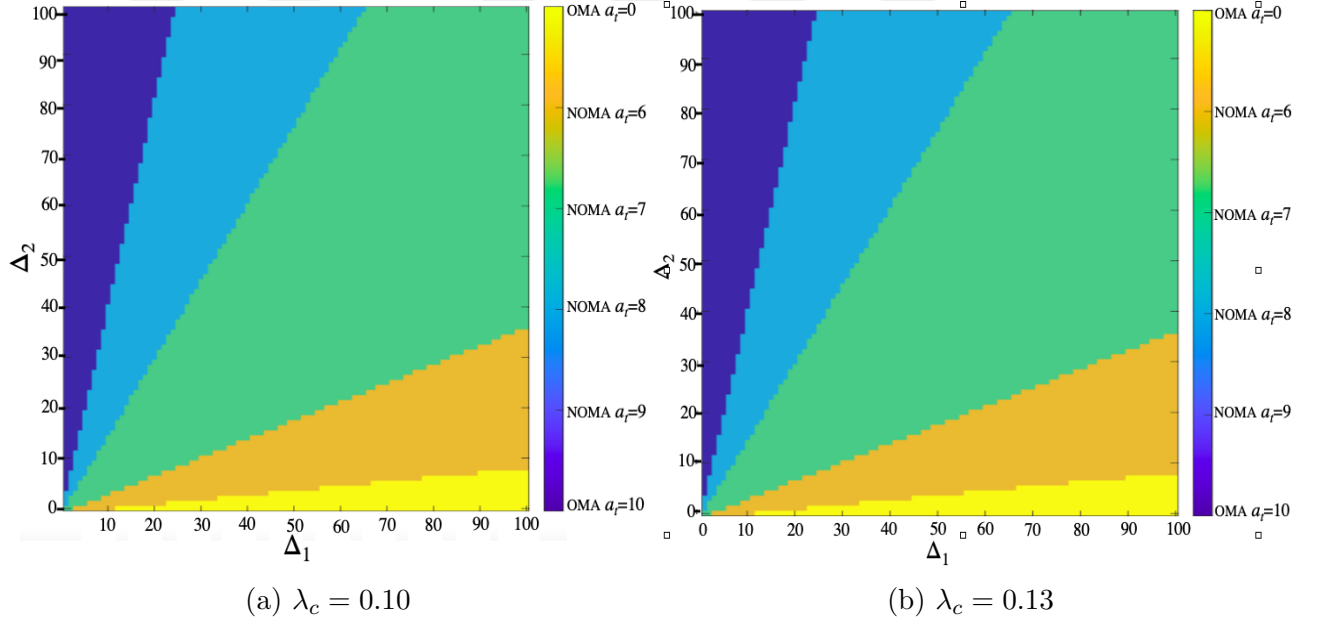


Figure 5.1: Adaptive policy with equal common target rates when $\lambda_{c,1} = \lambda_{c,2} = 0.10, 0.13$, $\rho = 18$ dB

Simulations are based on scenarios. We have defined two main scenarios:

- Target Rates of user 1 and user 2 are equal
- Target Rates of user 1 and user 2 are unequal

For parametric analysis, we need to change values of an independent parameter to be analysed while keeping all other independent parameters constant. In the first main scenario, effect of all parameters are analyzed one by one by changing the values of the parameter to be studied while keeping all the others constant.

Table 5.1: Scenarios for unequal target rates

	$R_1^* > R_2^*$	$R_2^* > R_1^*$
$w_1 > w_2$	X_1	X_2
$w_2 > w_1$	X_3	X_4

For the second main scenario, where both user target rates and user weights are unequal, we use various combinations of sub-scenarios that will analyze impact of parameters on the performance metrics under the R^* and w given in Table 5.1, where X_1, X_2, X_3, X_4 are the related performance metric values.

As explained in Chapter 4, some studies made on sub-optimal policy and optimal policy performances for NOMA and OMA schemes, (e.g. by [47, 55]), show that optimal/sub-optimal policy results are very close, especially at close user distances to BS, and at high SNR values. A similar study comparing performances of optimal and sub-optimal policies is made in this thesis, with addition of RSMA scheme. It is observed from Figure 5.2, Figure 5.3, and Figure 5.4 that sub-optimal policy for RSMA scheme provides results which are very close to the ones with optimal policy. According to Figure 5.4, there seems to be a small gap between the results at low SNR values. However, as seen in Figure 5.4, this gap increases when user distance is increased. The computation time of sub-optimal policy dropped to nearly one third of the computation time of optimal policy. Since computation complexity of sub-optimal policy is very low in comparison to optimal policy, computation time is substantially saved by using sub-optimal policy.

5.2 Impact of Target Rates on Adaptive Policy for Equal Target Rates

Target rate for the user i (R_i^*) consists of private target rate ($R_i^{*(p)}$) and common target rate ($R_i^{*(c)}$). Considering that $\lambda_{p,i} = R_i^{*(p)}/R_i^*$, $\lambda_{c,i} = R_i^{*(c)}/R_i^*$, and $\lambda_{p,i} + \lambda_{c,i} = 1$, a parametric study on $\lambda_{c,i}$ will give information also on the effect of $\lambda_{p,i}$.

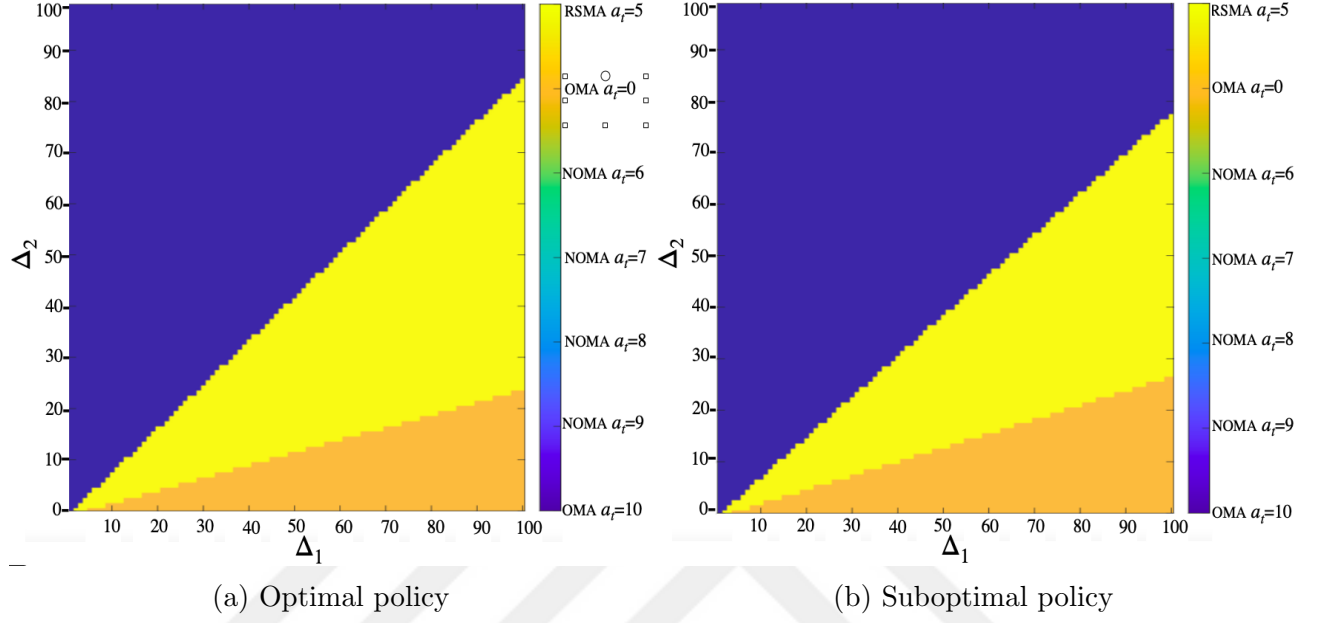


Figure 5.2: Optimal and suboptimal policy with equal common target rates when $\lambda_{c,1} = \lambda_{c,2} = 0.20$, $\rho = 12$ dB

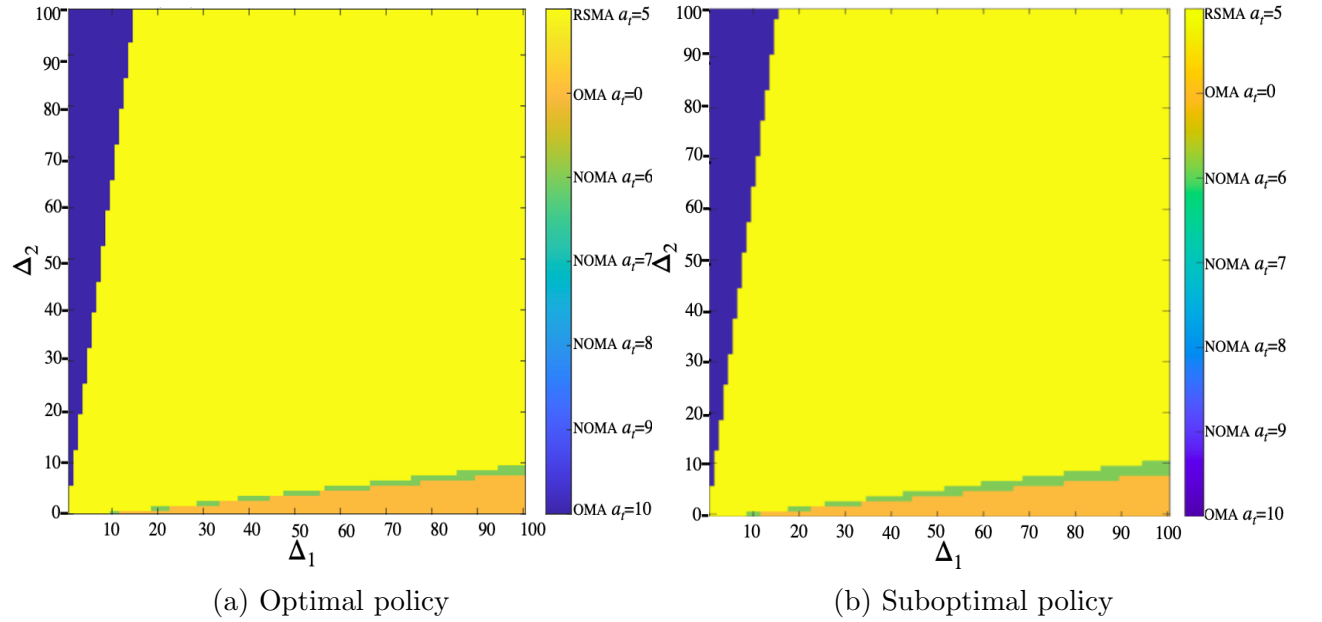


Figure 5.3: Optimal and suboptimal policy with equal common target rates when $\lambda_{c,1} = \lambda_{c,2} = 0.20$, $\rho = 18$ dB

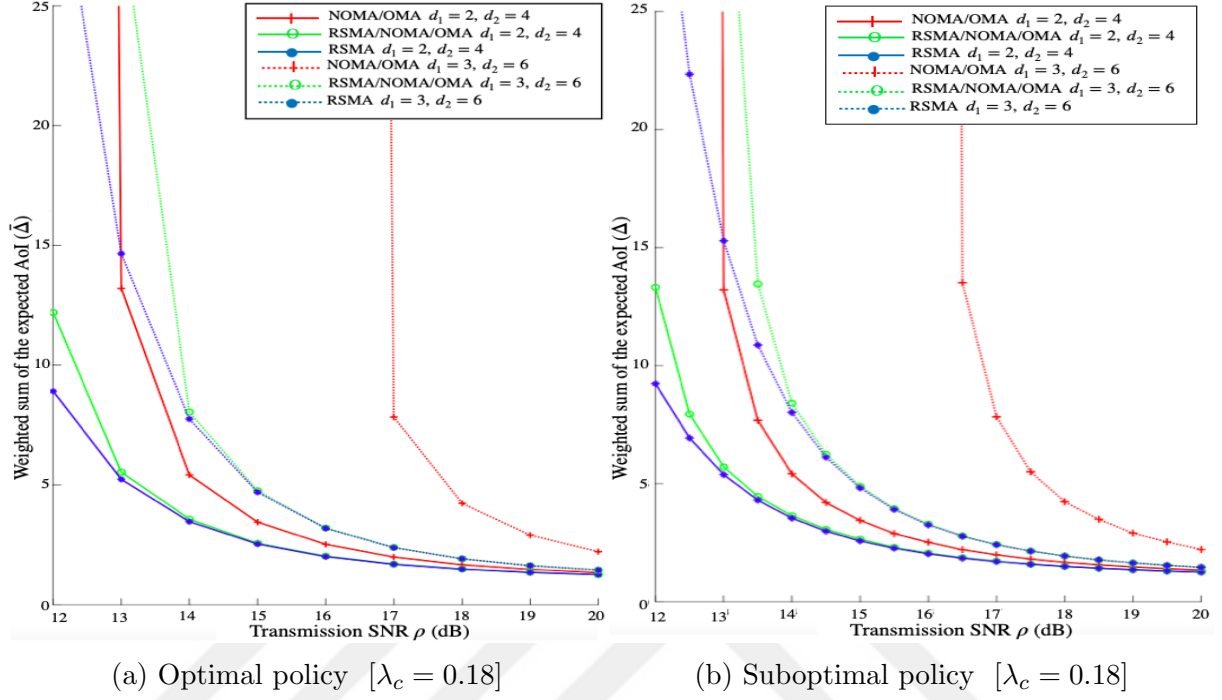


Figure 5.4: Impact of transmission SNR on WSAoI for optimal and suboptimal policy when far user's distance is changed) [$w_1 = w_2 = 0.5$]

Therefore, in this section, parametric study is done only for $\lambda_{c,i}$.

5.2.1 Impact of Common Target Rates on Adaptive Policy

Ratio of common target rate ($R_i^{*(c)}$) to the target rate (R_i^*), where i is 1 or 2, $\lambda_{c,1}, \lambda_{c,2}$, might be the same or different for user 1 and 2. In the analysis $\lambda_{c,1}$ or $\lambda_{c,2}$ values were taken as 0.10, 0.12, 0.13, 0.14, 0.15, 0.16, 0.17, 0.18, 0.19, and 0.20, where (0.10, 0.12, 0.13, and 0.14), (0.15, 0.16, 0.17, and 0.18), and (0.19 and 0.20) represent low, medium, and high level value groups, respectively.

Table 5.2: Simulation parameters for impact of equal common target rates

Parameter	Value
R_1^*, R_2^*	1
w_1, w_2	0.5
d_1, d_2	(2, 4), (3, 6)
$\lambda_{c,1}, \lambda_{c,2}$	(0.20, 0.20), (0.19, 0.19) (0.18, 0.18), (0.17, 0.17), (0.16, 0.16), (0.15, 0.15) (0.14, 0.14), (0.13, 0.13) (0.12, 0.12), (0.10, 0.10)
N	10
ρ in dB	18, 20

5.2.1.1 Equal Common Target Rates

In this scenario, effect of equal common target rates on the performance parameter, weight sum of the expected AoI, is studied, while keeping values of all other parameters as constant. The simulation results are shown in the related tables. The adaptive policy decisions for each case are also shown in colored graphs. Each point in the colored graph represents a selection decision for a state $s = (\Delta_1, \Delta_2)$. Adaptive policy with equal common target rates, user weights and transmission SNR under different values for common target rate, $R^{*(c)}$ is investigated. Ratio of common target rate ($R_i^{*(c)}$) to the target rate (R_i^*), where i is 1 or 2, $\lambda_{c,1}, \lambda_{c,2}$, is same for user 1 and 2, hence common target rates, $R_1^{*(c)} = R_2^{*(c)} = R^{*(c)}$. Simulation parameters for impact of common target rates, and simulation results for WSAoI under equal common target rate condition are given respectively in the Table 5.2, Figure 5.5 and Table 5.3. Adaptive RSMA/NOMA/OMA policy related to the Table 5.2 and Table 5.3 are given in Figure 5.1, Figure 5.6 and Figure 5.7 as 2-D colored graphs, and as percentages for user distances $d_1 = 2, d_2 = 4$ in Table 5.4 for user distances $d_1 = 3, d_2 = 6$ in Table 5.5. The colored graphs show the results only for transmission SNR, $\rho = 18$ dB and user distances $d_1 = 2, d_2 = 4$. The results for the transmission SNR, $\rho = 20$ dB and user distances $d_1 = 3, d_2 = 6$ are given in Appendix C.1.

According to Table 5.3 and Figure 5.5, when $\lambda_{c,1}$ and $\lambda_{c,2}$ are ≤ 0.15 , WSAoI is insensitive to the related λ_c and above the threshold value, it decreases with increasing λ_c . When age difference of two users is small, both users are served through RSMA or NOMA. If the common part of user message is high, RSMA

Table 5.3: WSAoI under equal common target rate condition and $[d_1 = 2, d_2 = 4]$

$\lambda_{c,1}, \lambda_{c,2}$	WSAoI	
	Transmission SNR $\rho = 18$ dB	Transmission SNR $\rho = 20$ dB
0.20, 0.20	1.4104	1.2230
0.19, 0.19	1.4504	1.2420
0.18, 0.18	1.4981	1.2641
0.17, 0.17	1.5583	1.2911
0.16, 0.16	1.6380	1.3281
0.15, 0.15	1.6716	1.3430
0.14, 0.14	1.6697	1.3430
0.13, 0.13	1.6697	1.3430
0.12, 0.12	1.6697	1.3430
0.10, 0.10	1.6697	1.3430

Table 5.4: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with equal common target rates $[d_1 = 2, d_2 = 4]$

$\lambda_{c,1} = \lambda_{c,2}$	Policy for all actions, %					
	SNR $\rho = 18$ dB			SNR $\rho = 20$ dB		
	OMA	NOMA	RSMA	OMA	NOMA	RSMA
0.10	16	84	0	8	92	0
0.12	16	84	0	8	92	0
0.13	16	84	0	8	92	0
0.14	16	84	0	8	92	0
0.15	16	81	3	8	87	5
0.16	15	33	52	8	38	54
0.17	14	12	74	8	16	76
0.18	14	8	78	6	10	84
0.19	12	4	84	5	7	88
0.20	11	1	88	5	3	92

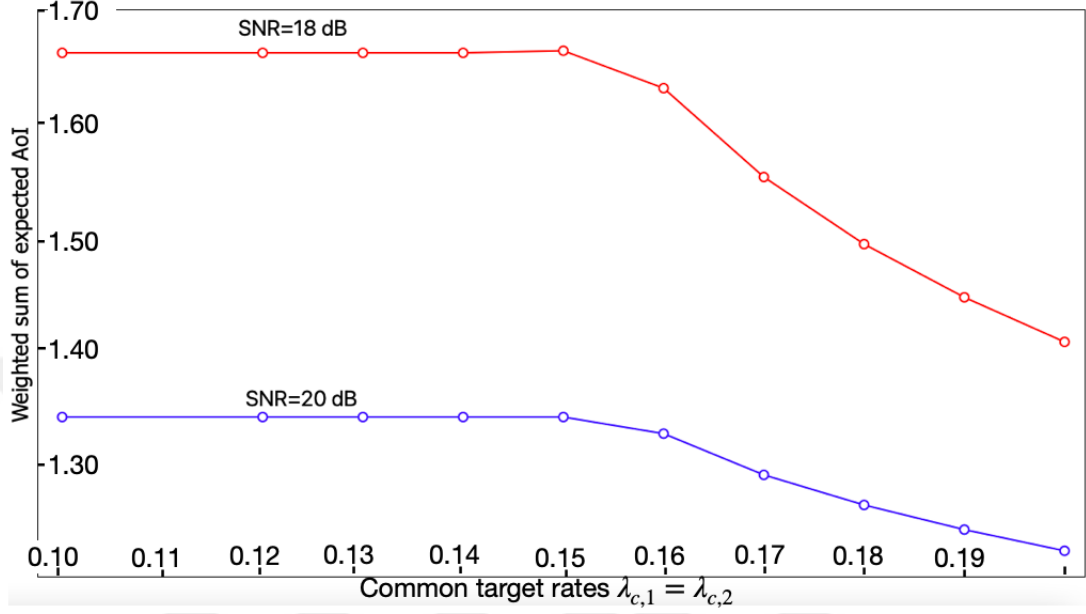


Figure 5.5: Age values for various equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = 0.10, 0.12, 0.15, 0.18, 0.20$) when transmission SNR $\rho = 18, 20$ dB, $[d_1 = 2, d_2 = 4]$

is selected. Otherwise, NOMA is used, and it is insensitive to λ_c below the threshold value. AoI decreases with increasing SNR. At high SNR values, BS can serve both users through RSMA or NOMA, and WSAoI decreases. This is due to the result that RSMA is not observed for common target rates under a threshold. Above this threshold value, an increase in λ_c leads to a decrease in WSAoI as RSMA is preferred, and both users are served at the same time. For example, for $\lambda_c = 0.20$ and $\lambda_c = 0.18$, the performance metric, WSAoI, is 16% and 10% better for RSMA than for NOMA/OMA cases. Regarding the transmission SNR, an increase in transmission SNR from 18 dB to 20 dB yields to a substantial decrease (13%-20%) in WSAoI. Above the threshold value, RSMA scheme is started to be selected by the adaptive policy, and its selection percentage increases with increasing λ_c . Above the threshold λ_c , OMA and NOMA selection by the adaptive policy decreases and RSMA selection increases with increasing λ_c , and RSMA dominates over NOMA/OMA for $\lambda_c > 0.15$.

In Figure 5.1, it is seen that RSMA mode is never selected for $\lambda_{c,1} = \lambda_{c,2} = 0.10$ and $\lambda_{c,1} = \lambda_{c,2} = 0.13$, since WSAoI is insensitive to the related λ_c , and the system is in OMA or NOMA mode. Considering the percentage of the colored

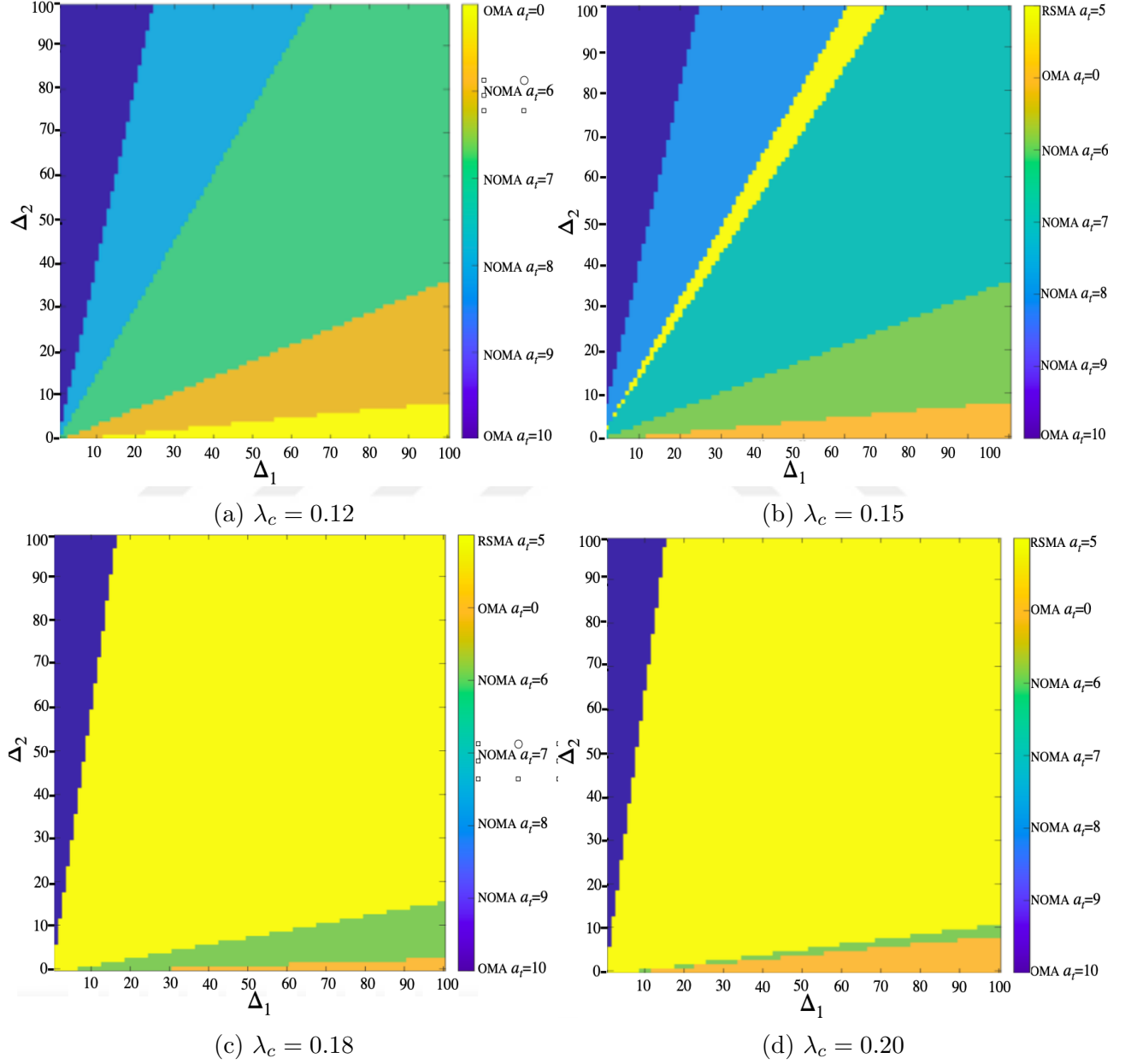


Figure 5.6: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.12, 0.15, 0.18, 0.20$) when transmission SNR $\rho = 18$ dB

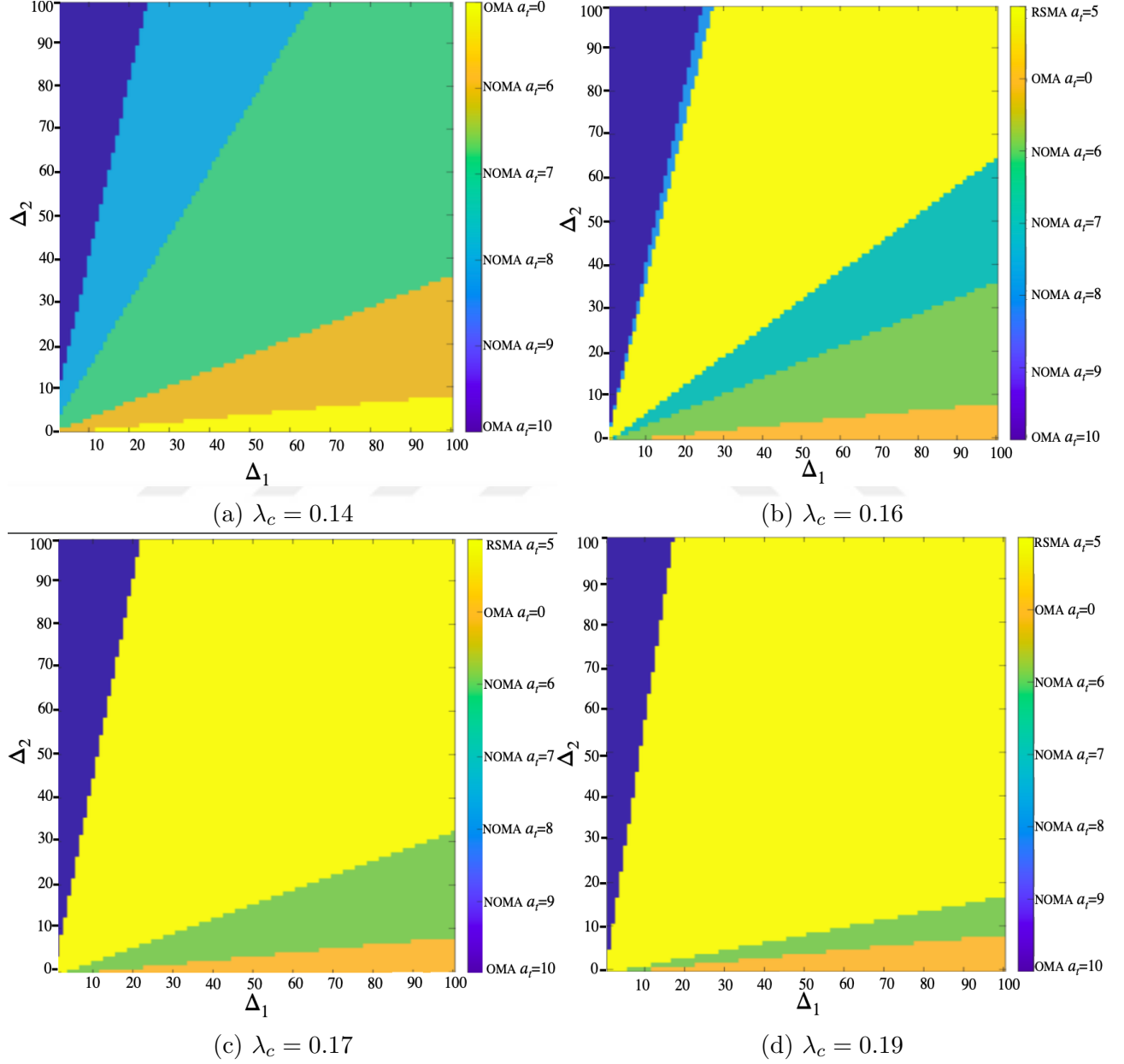


Figure 5.7: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.14, 0.16, 0.17, 0.19$) when transmission SNR $\rho = 18$ dB

Table 5.5: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with equal common target rates [$d_1 = 3, d_2 = 6$]

$\lambda_{c,1} = \lambda_{c,2}$	Policy for all actions, %					
	SNR $\rho = 18$ dB			SNR $\rho = 20$ dB		
	OMA	NOMA	RSMA	OMA	NOMA	RSMA
0.10	64	36	0	27	73	0
0.13	42	0	58	22	4	74
0.14	34	0	66	20	0	80
0.15	27	0	73	26	0	84
0.16	22	0	78	12	0	88
0.17	18	0	82	9	0	91
0.18	14	0	86	8	0	92
0.19	11	0	89	5	0	95

areas indicating OMA and NOMA, $\lambda_c = 0.10, \rho = 18$ dB, the adaptive policy takes the actions for OMA and NOMA, respectively 16% and 84% in all of the actions. However, these values are 8% and 92%, respectively, for $\rho = 20$ dB. It can be concluded from Table 5.4 that OMA decreases and NOMA increases with increasing transmission SNR, since outage probabilities for both users decreases, and capability for serving to both users increases with increasing SNR.

In Figure 5.6(a), it is seen that RSMA mode is never selected for $\lambda_{c,1} = \lambda_{c,2} = 0.12$, since WSAoI is insensitive to the related λ_c , and the system is in OMA or NOMA mode. Considering the percentage of the colored areas indicating OMA and NOMA, the adaptive policy takes the actions for OMA and NOMA, respectively 16% and 84% in all of the actions.

In Figure 5.6(b), $\lambda_{c,1} = \lambda_{c,2} = 0.15$, NOMA mode dominates over OMA and RSMA. When $\lambda_{c,1} = \lambda_{c,2} = \lambda_c$ increases, the mode selection gets in favor of RSMA mode. This is intuitive because the increase in common target rate results in a decrease in private target rate, that decreases outage probabilities for RSMA. Regarding the percentage of the colored areas indicating OMA, NOMA, and RSMA, the adaptive policy takes the actions for OMA, NOMA, and RSMA respectively 8%, 87%, and 5% in all of the actions. At that low level of λ_c , NOMA dominates over OMA and RSMA, and NOMA scheme selection increases with increasing SNR. However, increasing λ_c further, increases RSMA scheme

selection.

With Figure 5.6(c) and Figure 5.6(d), it is seen that RSMA mode is preferable when $\lambda_{c,1}$ and $\lambda_{c,2}$ are greater than the threshold (0.12). Considering the percentage of the colored areas of Figure 5.6(c) and Figure 5.6(d), RSMA dominates over OMA and NOMA with 84% and 91%, respectively in all of the actions.

Table 5.4 and Table 5.5 show that adaptive policy selects only NOMA/OMA for $\lambda_{c,1} = \lambda_{c,2} \leq 0.15$ when $d_1 = 2$, $d_2 = 4$. The threshold value decreases to 0.12 when the user distances are increased to $d_1 = 3$, $d_2 = 6$ since outage probability increases with increasing user distance, and OMA selection increases. Above the threshold value, RSMA scheme selection dominates over NOMA/OMA schemes. RSMA selection increases with increasing user common rate. RSMA domination becomes much obvious when the user distances are increased (for example, to $d_1 = 3$, $d_2 = 6$) since RSMA selection increases with increasing λ_c and SNR, which in turn yields to also increase in OMA selection against NOMA scheme. However, this is observed at high levels of SNR. At low level SNR, both RSMA and NOMA selection decreases but OMA scheme selection increases due to increasing outage probabilities. With increasing user distances to BS, RSMA and OMA sheme selection increases and NOMA scheme selection decreases. Below the threshold, NOMA scheme selection rate dominates over OMA scheme at small user distances and high SNR levels since outage probability will be low, and BS could serve both users simultaneously. However, this observation is not possible at higher user distances, or low SNR levels. Under the same conditions, RSMA or NOMA scheme selection percentage increases with increasing transmission SNR since at high level of SNR, BS can serve both users simultaneously. Depending on the level of λ_c either RSMA or NOMA dominates.

In summary, there is a threshold value for equal common rates above which adaptive policy starts to select RSMA, and RSMA selection percentage increases with increasing λ_c , while below the threshold either NOMA or OMA or both are selected, and OMA or NOMA scheme selection percentages depend on common target rate, user distance, and SNR. When RSMA is selected, the performance metric, WSAoI, is 16% and 10% better than NOMA/OMA cases. Regarding the

Table 5.6: Simulation parameters for impact of unequal common target rates

Parameter	Value
R_1^*, R_2^*	1
w_1, w_2	0.5
N	10
ρ	18 dB
$(\lambda_{c,1}, \lambda_{c,2})$	(0.20,0.18),(0.20,0.16),(0.20,0.14),(0.20,0.12),(0.20,0.10), (0.18,0.15),(0.18,0.12),(0.18,0.10), (0.18,0.20),(0.16,0.20), (0.14,0.20) (0.12,0.20),(0.10,0.20) , (0.15,0.18),(0.12,0.18), (0.10,0.18)

transmission SNR, an increase (58.4%) in transmission SNR yields to a decrease (13%-20%) in WSAoI.

5.2.1.2 Unequal Common Target Rates

In this scenario, effect of unequal common target rates on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Adaptive policy with different values for common target rate, $R^{*(c)}$ is investigated. Ratio of common target rate ($R_i^{*(c)}$) to the target rate (R_i^*), where i is 1 or 2, $\lambda_{c,1}, \lambda_{c,2}$, is different for user 1 and 2, hence common target rates, $R_1^{*(c)}$ and $R_2^{*(c)}$ are different. R_1^* and R_2^* are same and equal to 1 while $\lambda_{c,1}$ and $\lambda_{c,2}$ are different. Common target rates ($R_i^{*(c)}$) are defined by using λ_c since R_i^* is constant. Simulation parameters and results of simulations for the impact of common target rates on WSAoI under unequal common target rate condition are given respectively in the Table 5.6 and Table 5.7.

Adaptive RSMA/NOMA/OMA policy related to the Table 5.6 and Table 5.7 are given in Figure 5.8 as 2-D colored graphs. Only four of the cases, two cases with $\lambda_{c,1} > \lambda_{c,2}$ and the other two cases with $\lambda_{c,2} > \lambda_{c,1}$, are given here. In these figures, the transmission SNR $\rho = 0.18$. The figures for the rest of 32 cases for which $\rho = 0.18$ or $\rho = 0.20$ are given in Appendix C.2.

Table 5.7 also reflects the trade-off between the user distance and $\lambda_{c,1}, \lambda_{c,2}$.

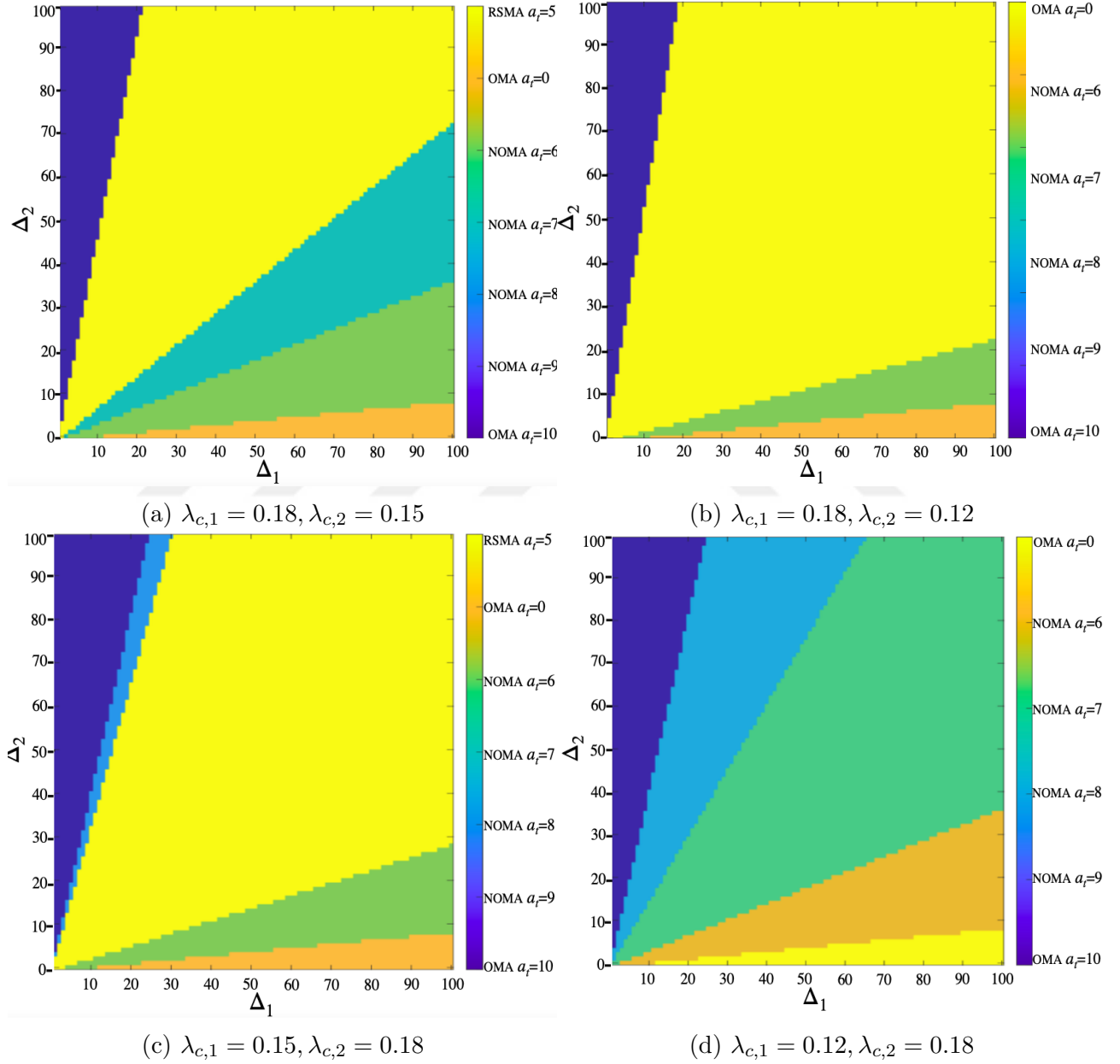


Figure 5.8: Adaptive policy with unequal common target rates when transmission SNR $\rho = 18$ dB

Table 5.7: WSAoI under unequal common target rate condition

$\lambda_{c,1}, \lambda_{c,2}$	WSAoI	
	Transmission SNR $\rho = 18$ dB	Transmission SNR $\rho = 20$ dB
0.20, 0.18	1.4670	1.2495
0.20, 0.16	1.5649	1.2940
0.20, 0.14	1.6525	1.3352
0.20, 0.12	1.6649	1.3430
0.20, 0.10	1.6697	1.3430
0.18, 0.15	1.6425	1.3297
0.18, 0.12	1.6697	1.3430
0.18, 0.10	1.6697	1.3430
0.18, 0.20	1.4398	1.2369
0.16, 0.20	1.4781	1.2546
0.14, 0.20	1.5332	1.2783
0.12, 0.20	1.6174	1.3202
0.10, 0.20	1.6702	1.3432
0.15, 0.18	1.5685	1.2956
0.12, 0.18	1.6696	1.3430
0.10, 0.18	1.6697	1.3430

In Table 5.7, $\lambda_{c,1}$ is larger than $\lambda_{c,2}$ in the first eight rows of the table, while $\lambda_{c,2}$ is larger than $\lambda_{c,1}$ in the remaining eight rows.

According to Table 5.7, when $\lambda_{c,1}$ or $\lambda_{c,2}$ is ≤ 0.12 , WSAoI is insensitive to the related λ_c . Because λ_c is very low for one user, RSMA scheme is not applicable, and since user distances and common target rates are different, outage probability of one user may increase. This increase yields to OMA scheme. After OMA selection, difference between the ages of two users will decrease, and this may result in NOMA scheme selection for which BS allocates power to both users but at different levels. Effect of each scheme on WSAoI is balanced by the application of the other scheme. Above the threshold value, an increase in one user's λ_c while keeping the other's constant leads to a decrease in WSAoI, since RSMA scheme will start to dominate, for which BS serves both users together, when outage probability of one user increases, the policy selects OMA scheme which will decrease the age for this user. Serving both users simultaneously with increasing, and using OMA for the user with high outage probability decreases

WSAoI.

We can understand that, when $\lambda_{c,1}$ or $\lambda_{c,2}$ is less than or equal to the threshold, a decrease in common target ratio increases the likelihood of the outage event and increases WSAoI where the system could select RSMA mode. This is due to the fact that the system is in NOMA or OMA mode for $\lambda_{c,1}$ or $\lambda_{c,2} \leq 0.12$, and the ages of the users are not a function of the related λ_c . Above the threshold value, RSMA scheme is selected by the adaptive policy. While keeping $\lambda_{c,1} = 0.18$ constant, an increase in $\lambda_{c,2}$ from 0.12 to 0.15 decreases the performance metric, WSAoI, by 1.6%. However, while keeping $\lambda_{c,2} = 0.18$ constant, an increase in $\lambda_{c,1}$ from 0.12 to 0.15 decreases the performance metric by 6%. This shows that an increase in λ_c of the user 1 while keeping the other user's λ_c constant is more effective in decreasing the performance metric than the vice versa. Being able to service to both users together yields to less WSAoI than servicing to only one user at a time. Increasing far user's λ_c increases its outage probability, and forces BS to serve the far user in OMA mode. However, in case of increasing rear user's λ_c , outage probability for the far user with higher λ_c will be less in comparison to the previous case. The stated improvements are also due to change from OMA/NOMA to RSMA. Regarding the transmission SNR, an increase in transmission SNR yields to a substantial decrease (18%-20%) in WSAoI, since at high SNR, BS can serve both users simultaneously with a low outage probability. The adaptive RSMA/NOMA/OMA policy related to the Table 5.6 and Table 5.7 are given in Figure 5.8 as 2-D colored graphs. The colored graphs show the results only for transmission SNR, $\rho = 18$ dB.

According to Figure 5.8, it is seen that RSMA mode is preferable when $\lambda_{c,1}$ or $\lambda_{c,2}$ are greater than the threshold (0.12). Increasing common part of the message increases the likelihood of RSMA scheme selection. This also depends on SNR level. At high SNR levels, BS can serve both users simultaneously. Considering the percentage of the colored areas of Figure 5.8(a) and Figure 5.8(c), RSMA scheme dominates over OMA and NOMA schemes with 53% and 71%, respectively in all of the actions.

In Figure 5.8(b) and Figure 5.8(d), respectively ($\lambda_{c,1} = 0.18, \lambda_{c,2} = 0.12$) and

Table 5.8: Simulation parameters for impact of user weights

Parameter	Value
R_1^*, R_2^*	1
(w_1, w_2)	(0.3,0.7),(0.4,0.6),(0.6,0.4),(0.7,0.3)
$\lambda_{c,1} = \lambda_{c,2}$	0.18, 0.12
N	10
ρ	18 dB, 20 dB

Table 5.9: WSAoI under unequal user weight distribution

User weights	WSAoI			
	Transmission SNR $\rho = 18$ dB		Transmission SNR $\rho = 20$ dB	
	$\lambda_{c,1}=\lambda_{c,2}=0.18$	$\lambda_{c,1}=\lambda_{c,2}=0.12$	$\lambda_{c,1}=\lambda_{c,2}=0.18$	$\lambda_{c,1}=\lambda_{c,2}=0.12$
$w_1=0.3, w_2=0.7$	1.6246	1.7468	1.3281	1.3731
$w_1=0.4, w_2=0.6$	1.5496	1.7030	1.2896	1.3604
$w_1=0.5, w_2=0.5$	1.4981	1.6657	1.2641	1.3430
$w_1=0.6, w_2=0.4$	1.4690	1.6646	1.2474	1.3298
$w_1=0.7, w_2=0.3$	1.4524	1.6594	1.2327	1.3125

($\lambda_{c,1} = 0.12, \lambda_{c,2} = 0.18$), NOMA mode dominates over OMA and RSMA (0%), since in both cases λ_c of one user is equal to the threshold value 0.12. Regarding the percentage of the colored areas indicating OMA, NOMA, and RSMA, the adaptive policy takes the actions for OMA, NOMA, respectively 16% and 84% in all of the actions.

5.2.2 Impact of User Weight Distribution on Adaptive Policy

In this scenario, effect of user weight on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant. Adaptive policy with different values for user weights, w_1 and w_2 is investigated. Since $w_1 + w_2 = 1$, increasing user 1's weight yield to a related decrease in user 2's weight.

Simulation parameters for the impact of user weights and WSAoI under unequal user weight distribution are illustrated in the Table 5.8 and Table 5.9.

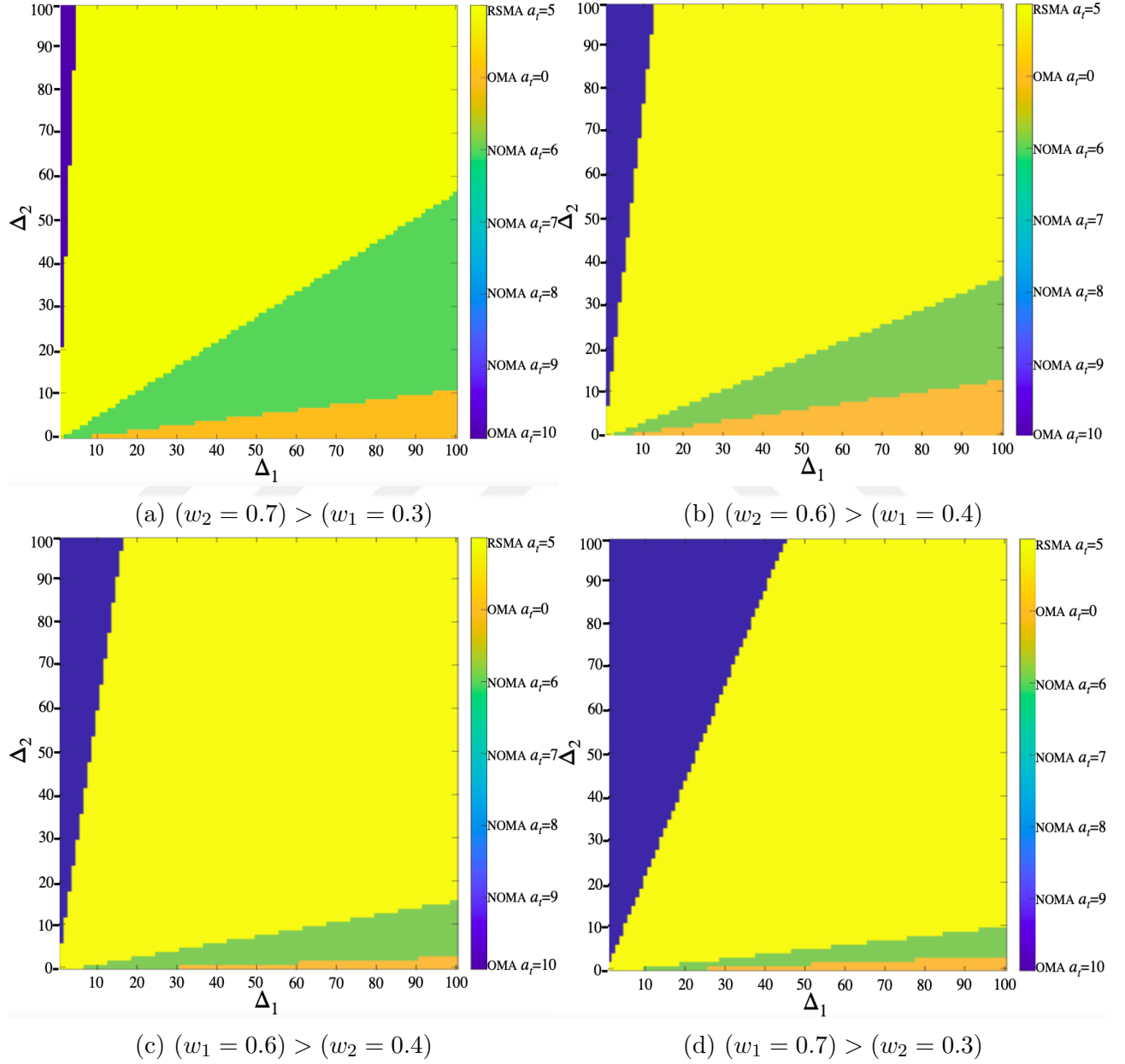


Figure 5.9: Adaptive policy with unequal user weights when transmission SNR $\rho = 18$ dB

According to Table 5.9, increasing user 1's weight, who is at closer distance from BS, (decreases user 2's weight accordingly), decreases WSAoI since decreasing weight of far user reduces contribution of the far user in WSAoI, and in turn reduces WSAoI. An change from $w_1 = 0.3$ ($w_2 = 0.7$) to $w_1 = 0.7$ ($w_2 = 0.3$) yields to 7%-10% decrease in WSAoI. For the same unequal user weight state, an increase in transmission SNR (ρ) results in 10%-15% decrease in WSAoI since an increase in SNR increases capability of BS serving both users at the same time, and decreases outage probability.

Figure 5.9 shows that more power is allocated to user with greater user weight. If far user (user 2) has greater weight, the policy tries to increase α_2 . The system mode becomes in favor of OMA when α_1 or α_2 takes values close to 1.

According to Figure 5.9, it is seen that RSMA mode dominates over NOMA/OMA mode. When SNR is high, the BS can serve both users together, which increases selection probability of RSMA or NOMA. In Figure 5.9 RSMA dominates over NOMA since λ_c is high. However, serving both users together may increase outage probability of the user in worse condition, which in turn yields to selection of OMA scheme for the related user. When $w_1 \leq 0.5$ ($w_2 > 0.5$), RSMA preference increases with increasing w_1 (decreasing w_2) since decreasing weight of far user that requires higher power allocation increases the probability of serving both users together through either RSMA or NOMA, and when the λ_c is high, RSMA dominates over NOMA. However, when $w_1 > 0.5$ ($w_2 < 0.5$), RSMA preference decreases with increasing w_1 (decreasing w_2) since far user's outage probability increases with decreasing w_2 , which in turn yields to OMA scheme selection and slight decrease in RSMA domination over NOMA. Considering the percentage of the colored areas in Figure 5.9, RSMA dominates over OMA and NOMA with increasing percentages of 70% and 77% in Figure 5.9(a) and Figure 5.9(b), while with decreasing percentages of 79% and 73 % in Figure 5.9(c) and Figure 5.9(d), respectively in all of the actions.

5.2.3 Impact of User Distance from Base Station on Adaptive Policy

In this scenario, impact of user distance from BS on the performance metric, weight sum of the expected AoI, is studied, while keeping values of all other parameters as constant.

Adaptive policy is investigated under different values for distances of user 1 and user 2 from BS, d_1 and d_2 , respectively. Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI under unequal user distance distribution are given respectively in the Table 5.10 and Table 5.11.

Adaptive RSMA/NOMA/OMA policy related to the Table 5.10 and Table 5.11 is given in Figure 5.10 and Figure 5.11 for an example case, for $(d_1 = 2, d_2 = 4)$ and $(d_1 = 3, d_2 = 6)$, respectively. Detailed studies are given in Section 5.4.

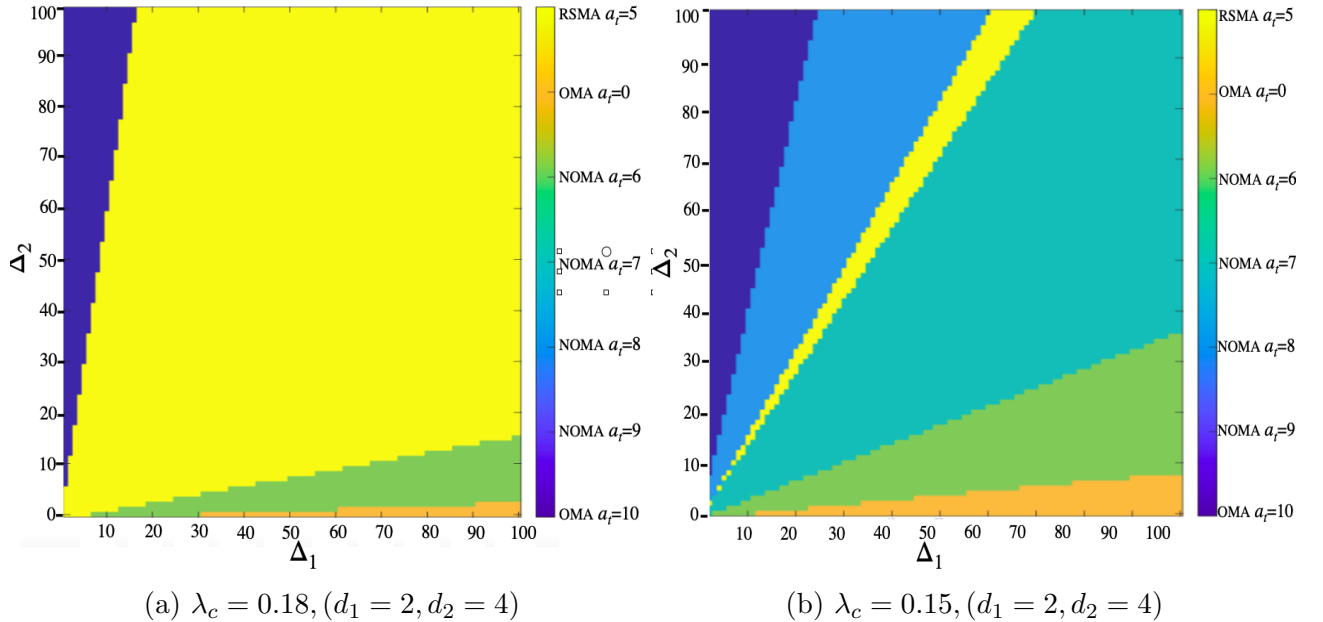


Figure 5.10: Adaptive policy with unequal user distances ($d_1 = 2$, $d_2 = 4$) [SNR $\rho = 18$ dB, $w_1 = w_2 = 0.5$]

The adaptive RSMA/NOMA/OMA policy related to the Table 5.8 and Table 5.9 are given in Figure 5.9 as 2-D colored graphs for the scenarios where $\lambda_1 =$

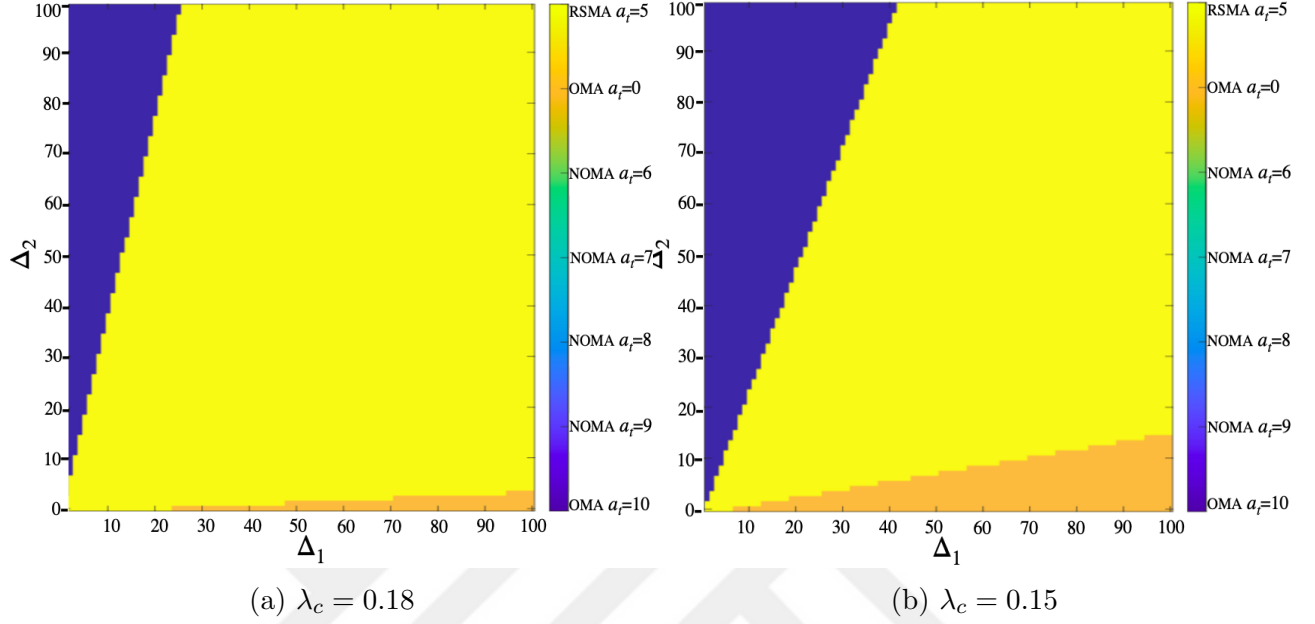


Figure 5.11: Adaptive policy with unequal user distances, ($d_1 = 3$, $d_2 = 6$) [SNR $\rho = 18$ dB, $w_1 = w_2 = 0.5$]

$\lambda_2 = 0.18$ and the transmission SNR $\rho = 0.18$. The figures for other scenarios are given in Appendix C.3.

Figure 5.10 shows that RSMA scheme outperforms NOMA/OMA scheme for the user distances ($d_1 = 2$, $d_2 = 4$) when $\lambda_c = 0.18$, with the percentages of 76% and 24%, respectively. However, NOMA/OMA scheme outperforms RSMA scheme when $\lambda_c = 0.15$ since at low values of λ_c , RSMA scheme selection decreases.

Figure 5.11 shows that increasing user distances from ($d_1 = 2$, $d_2 = 4$) to ($d_1 = 3$, $d_2 = 6$) increases RSMA selection probabilities. Increasing the user distances to BS, increases also the distance between the rear and far users, which requires to increase power to be allocated to far user further. This, in turn, reduces the age difference between the users, and yields BS to serve both users simultaneously. RSMA scheme is preferred over NOMA scheme when λ_c is over a threshold value, and this threshold decreases with increasing user distances. RSMA scheme outperforms NOMA/OMA scheme for the user distances ($d_1 = 3$, $d_2 = 6$) when $\lambda_c = 0.18$, with the percentages of 86% and 14%, respectively.

Table 5.10: Simulation parameters for impact of user distances from BS

Parameter	Value
R_1^*, R_2^*	1
(d_1, d_2)	(2,4),(3,6)
$\lambda_{c,1} = \lambda_{c,2}$	0.15, 0.18
N	10
SNR ρ in dB	14,16,18,20

Table 5.11: WSAoI under different user distances from BS

User distances	WSAoI			
	Transmission SNR ρ in dB			
	$\rho=14$	$\rho=16$	$\rho=18$	$\rho=20$
$d_1=2, d_2=4$	3.5556	2.1111	1.6667	1.2222
$d_1=3, d_2=6$	7.9444	3.2222	2.2222	1.5566

When $\lambda_c = 0.15$, although NOMA/OMA schemes outperform RSMA at user distances $d_1 = 2, d_2 = 4$, it is the reverse at user distances $d_1 = 3, d_2 = 6$ with 73% and 27% for RSMA and NOMA/OMA, respectively (for transmission SNR=18 dB).

Table 5.11 shows that increasing the user distances from BS increases WSAoI. However, this effect is alleviated with increasing transmission SNR ρ . The increase in WSAoI with increase in user distances from $(d_1 = 2, d_2 = 4)$ to $(d_1 = 3, d_2 = 6)$ is 55% when transmission SNR is 14 dB. However, the increase in WSAoI is only 21% when SNR is 20 dB.

5.2.4 Impact of Transmission Signal to Noise Ratio on Adaptive Policy

In this scenario, transmission SNR, ρ , on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Impact of transmission SNR ρ is investigated under different user distances. Simulation parameters and results of simulations for transmission SNR impact

Table 5.12: Simulation parameters for impact of transmission SNR

Parameter	Value
$\lambda_{c,1}, \lambda_{c,2}$	(0.20, 0.20), (0.18, 0.18) (0.18, 0.15), (0.15, 0.18)
w_1, w_2	(0.4, 0.6), (0.6, 0.4)
(d_1, d_2)	(2, 4), (3, 6)
N	10
SNR in dB	18, 20

Table 5.13: WSAoI under different transmission SNR (ρ)

Parameter	WSAoI	
	Transmission SNR ρ in dB	
	$\rho=18$	$\rho=20$
$\lambda_{c,1}=0.20, \lambda_{c,2}=0.20$	1.4104	1.2641
$\lambda_{c,1}=0.18, \lambda_{c,2}=0.18$	1.4981	1.2230
$\lambda_{c,1}=0.18, \lambda_{c,2}=0.15$	1.6425	1.3297
$\lambda_{c,1}=0.15, \lambda_{c,2}=0.18$	1.5685	1.2956
$w_1=0.4, w_2=0.6$	1.5496	1.2896
$w_1=0.6, w_2=0.4$	1.4690	1.2474
$d_1=2, d_2=4$	1.6667	1.2222
$d_1=3, d_2=6$	2.2222	1.5556

on the performance metric, WSAoI under different conditions are illustrated in the Table 5.12 and Table 5.13. Age-energy tradeoff related to the Table 5.12 is shown in Figure 5.12.

Table 5.13 shows that an increase in transmission SNR ρ while keeping the other parameters constant yields to a decrease in the performance metric, WSAoI. For example, under the state conditions for common target ratio ($\lambda_{c,1} = 0.15, \lambda_{c,2} = 0.18$), or user weight of ($w_1 = 0.6, w_2 = 0.4$), or user distance of ($d_1 = 3, d_2 = 6$), increasing transmission SNR from $\rho = 0.18$ to $\rho = 0.20$ yields to decrease in WSAoI; 17%, 15%, and 30%, respectively. As BS can serve both users together when SNR is high, which yields to a decrease in WSAoI.

Figure 5.12 shows that when $\lambda_c = 0.18$ RSMA outperforms NOMA/OMA at all ranges of transmission SNR (ρ) (0.12 - 0.20) for all user distances $\{(d_1 =$

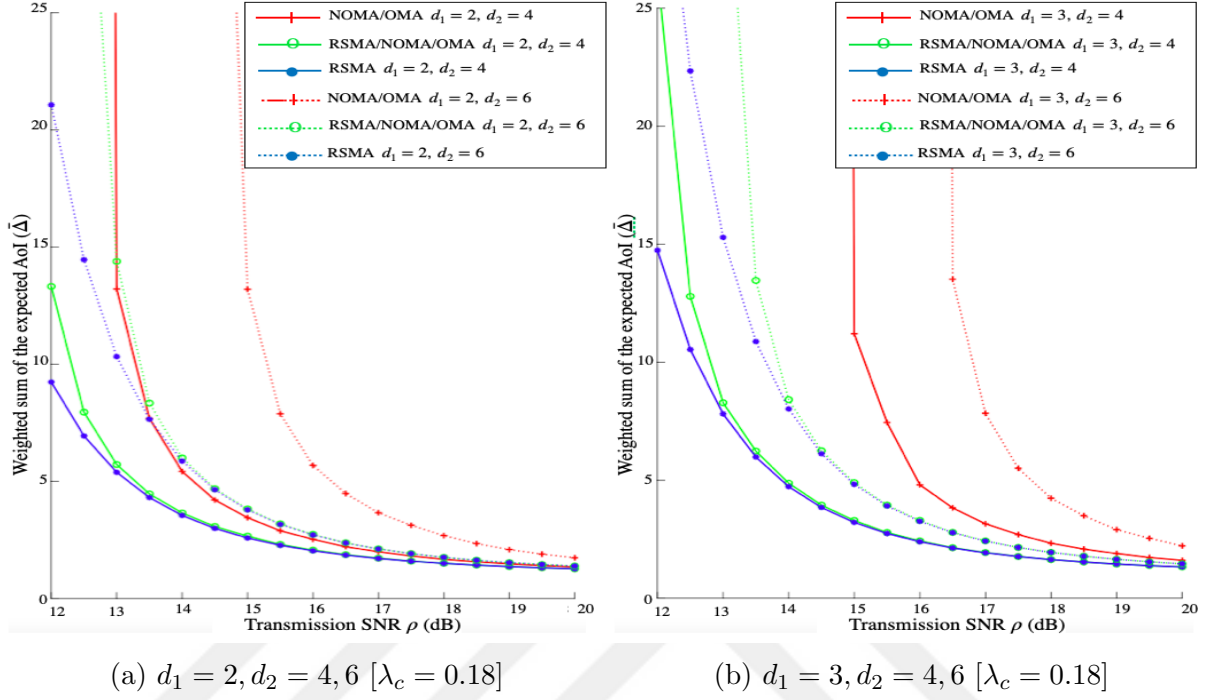


Figure 5.12: Impact of transmission SNR on WSAoI when far user's distance is changed) [$w_1 = w_2 = 0.5$]

$2, d_2 = 4$), $(d_1 = 2, d_2 = 6)$, $(d_1 = 3, d_2 = 4)$, $(d_1 = 3, d_2 = 6)$. When SNR is increased, capability of BS to serve both users simultaneously increases, which in turn increases RSMA and NOMA selection probabilities. Above a certain value of λ_c , which decreases with increasing user distances, RSMA scheme selection dominates over NOMA.

5.3 Impact of Target Rates on Adaptive Policy for Unequal Target Rates

In this main scenario, we have many sub-scenarios that will analyze impact of various parameters on performance metric, WSAoI, under unequal user rates. A user rate has private and common parts, R_p^* , R_c^* , where $R_1^* = R_{p,1}^* + R_{c,1}^*$ and $R_2^* = R_{p,2}^* + R_{c,2}^*$ respectively for user 1 and user 2. Combinations of scenarios are briefly shown in Table 5.14.

Table 5.14: Scenarios for unequal target rates and user weights without values

	$R_1^* > R_2^*$		$R_2^* > R_1^*$	
$w_1 > w_2$	$R_{c,1}^* = \text{constant}$	$R_{p,1}^* > R_{p,2}^*$	$R_{c,2}^* = \text{constant}$	$R_{p,2}^* > R_{p,1}^*$
	$R_{p,1}^* = \text{constant}$	$R_{c,1}^* > R_{c,2}^*$	$R_{p,2}^* = \text{constant}$	$R_{c,2}^* > R_{c,1}^*$
$w_2 > w_1$	$R_{c,1}^* = \text{constant}$	$R_{p,1}^* > R_{p,2}^*$	$R_{c,2}^* = \text{constant}$	$R_{p,2}^* > R_{p,1}^*$
	$R_{p,1}^* = \text{constant}$	$R_{c,1}^* > R_{c,2}^*$	$R_{p,2}^* = \text{constant}$	$R_{c,2}^* > R_{c,1}^*$

Table 5.15: Simulation parameters for unequal target and user rates for $R_1^* > R_2^*$

Parameter	Value
R_1^*, R_2^*	(1.0,0.8)
$R_{c,1}^*, R_{c,2}^*$	(0.10,0.10),(0.12,0.12),(0.15,0.15), (0.18,0.18),(0.20,0.20) (0.30,0.10),(0.32,0.12),(0.35,0.15), (0.38,0.18),(0.40,0.20)
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
ρ	12 dB
d_1, d_2	(2,4)

Analysis with scenarios for $R_1^* > R_2^*$ and $R_2^* > R_1^*$ cases are studied with simulation parameters given respectively in Table 5.15 and Table 5.17. Results of related simulations are illustrated respectively in Table 5.16 and Table 5.18.

5.3.1 Impact of Target Rates on Adaptive Policy

When the common target rate is increased or private target rate is decreased, whatever the user target rates and user weights are, BS will serve both users at the same time, and WSAoI will decrease accordingly. However, the decrease in WSAoI changes with the values of user target rates and user weights. Since target rate is decomposed into common and private target rates, the ratio of common target rate to target rate, λ_c , should be considered. In this respect, increase of λ_c results in decrease in WSAoI. For the specific case where $R_1^* > R_2^*$ and $w_1 > w_2$, increasing R_c^* or decreasing R_p^* , that is increasing λ_c , yields to a decrease in WSAoI. Increasing R_c^* is more effective on reducing WSAoI than

Table 5.16: WSAoI under unequal user target rates and user weights when $R_1^* = 1.0 > R_2^* = 0.8$

WSAoI		
	User weights $w_1 = 0.7 > w_2 = 0.3$	$w_2 = 0.7 > w_1 = 0.3$
$R_{c,1}^* = R_{c,2}^* = 0.10$	49.6442	8.9763
$R_{c,1}^* = R_{c,2}^* = 0.12$	21.2323	6.0037
$R_{c,1}^* = R_{c,2}^* = 0.15$	8.8931	3.9967
$R_{c,1}^* = R_{c,2}^* = 0.18$	4.1667	3.0333
$R_{c,1}^* = R_{c,2}^* = 0.20$	3.1345	2.6058
$R_{p,1}^* = R_{p,2}^* = 0.70$	2.5849	3.4785
$R_{p,1}^* = R_{p,2}^* = 0.68$	2.3119	3.0381
$R_{p,1}^* = R_{p,2}^* = 0.65$	2.0060	2.5233
$R_{p,1}^* = R_{p,2}^* = 0.62$	1.8333	2.1666
$R_{p,1}^* = R_{p,2}^* = 0.60$	1.6977	1.9288

Table 5.17: Simulation parameters for unequal target and user rates for $R_2^* > R_1^*$

Parameter	Value
R_1^*, R_2^*	(0.8, 1.0)
$R_{c,1}^*, R_{c,2}^*$	(0.10, 0.10), (0.12, 0.12), (0.15, 0.15), (0.18, 0.18), (0.20, 0.20)
	(0.10, 0.30), (0.12, 0.32), (0.15, 0.35), (0.18, 0.38), (0.20, 0.40)
w_1, w_2	(0.7, 0.3), (0.3, 0.7)
N	10
ρ	12 dB
d_1, d_2	(2, 4)

Table 5.18: WSAoI under unequal user target rates and user weights when $R_1^* = 0.8 < R_2^* = 1.0$

WSAoI		
	User weights $w_1 = 0.7 > w_2 = 0.3$	$w_2 = 0.7 > w_1 = 0.3$
$R_{c,1}^* = R_{c,2}^* = 0.10$	159.5320	45.5747
$R_{c,1}^* = R_{c,2}^* = 0.12$	56.3019	12.2916
$R_{c,1}^* = R_{c,2}^* = 0.15$	7.0616	5.2217
$R_{c,1}^* = R_{c,2}^* = 0.18$	4.0333	3.6667
$R_{c,1}^* = R_{c,2}^* = 0.20$	3.1274	2.8555
$R_{p,1}^* = R_{p,2}^* = 0.70$	2.6116	3.4785
$R_{p,1}^* = R_{p,2}^* = 0.68$	2.3364	3.0381
$R_{p,1}^* = R_{p,2}^* = 0.65$	2.0060	2.5233
$R_{p,1}^* = R_{p,2}^* = 0.62$	1.8333	2.1666
$R_{p,1}^* = R_{p,2}^* = 0.60$	1.6977	1.9288

decreasing R_p^* . The adaptive RSMA/NOMA/OMA policy related to the Table 5.15 and Table 5.16, where $R_1^* > R_2^*$, are given in Figure 5.13 for ($R_1^* = 1.0$, $R_2^* = 0.8$, $R_{c,1}^* = R_{c,2}^* = 0.2$) SNR $\rho = 12.5$ and 15.5 dB, as 2-D colored graphs. Only two examples of the scenarios are given in Figure 5.13. The rest of the related figures are given in Appendix C.4. Considering the percentage of the colored areas in Figure 5.13, RSMA scheme dominates over OMA and NOMA schemes with increasing percentages of 83% and 95%, respectively in all of the actions. In the scenario of Figure 5.13, $\lambda_{c,1} = 0.2$, $\lambda_{c,2} = 0.25$. At high λ_c values, RSMA dominates over NOMA. At low SNR value, outage probability of far user is high since not only the SNR, but also both target rate and user weight of far user are low, which in turn increases probability of OMA scheme for the far user. However, at a high SNR value, since BS can serve both users together, and λ_c is high, RSMA scheme dominates over NOMA, and OMA scheme selection probability decreases.

When $R_2^* > R_1^*$ and $w_2 > w_1$, the adaptive RSMA/NOMA/OMA policy related to the Table 5.17 and Table 5.18, where $R_2^* > R_1^*$, are shown in Figure 5.14 for ($R_1^* = 0.8$, $R_2^* = 1.0$, $R_{c,1}^* = R_{c,2}^* = 0.2$) SNR $\rho = 12$ and 13 dB, as 2-D colored graphs. Only two examples of the scenarios are given in Figure 5.14. In scenario of Figure 5.14, $\lambda_{c,1} = 0.25$, $\lambda_{c,2} = 0.20$. At high λ_c values, RSMA dominates over NOMA. At low SNR value, outage probability of far user is not high since both target rate and user weight of the far user are high, which in turn decreases the probability of OMA scheme for the far user. However, at a high SNR value, since BS can serve both users together, and λ_c is high, RSMA scheme dominates over NOMA, and OMA scheme selection probability decreases. The rest of the related figures are given in Appendix C.4. When $R_1^* < R_2^*$ and $w_1 < w_2$, increasing R_c^* or decreasing R_p^* yields to a decrease in WSAoI. Increasing R_c^* is more effective on reducing WSAoI than decreasing R_p^* .

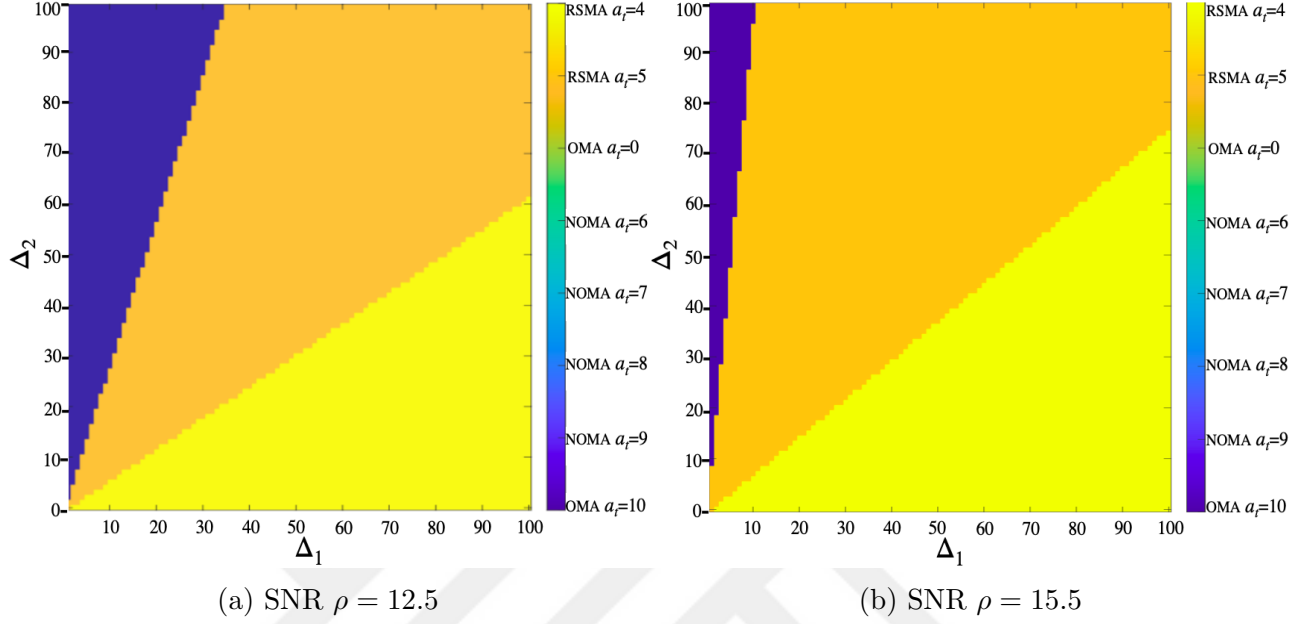


Figure 5.13: Adaptive policy with unequal target rates and user weights $[(R_1^* = 1.0, R_2^* = 0.8), (w_1 = 0.7, w_2 = 0.3), (R_{c,1}^* = R_{c,2}^* = 0.2)]$

5.3.2 Impact of User Weights on Adaptive Policy

WSAoI decreases if weight of the user with higher λ_c is increased when $R_1^* > R_2^*$, and if weight of the user with lower λ_c is increased when $R_2^* > R_1^*$. When $w_1 < w_2$, WSAoI is much less than for the case $w_1 > w_2$. Impact of user weight on reducing WSAoI is more effective when user's common rates are high, or private rates low.

Considering the adaptive policy, increasing the weight of the user with higher target rate increases the capability of BS to serve both users. RSMA and NOMA scheme selection percentages depend on λ_c , and when it increases RSMA scheme selection probability increases. However, serving both users may increase the age difference between the users, that will yield to increase in outage probability of the user in worse conditions, which in turn result in OMA scheme selection for the related user.

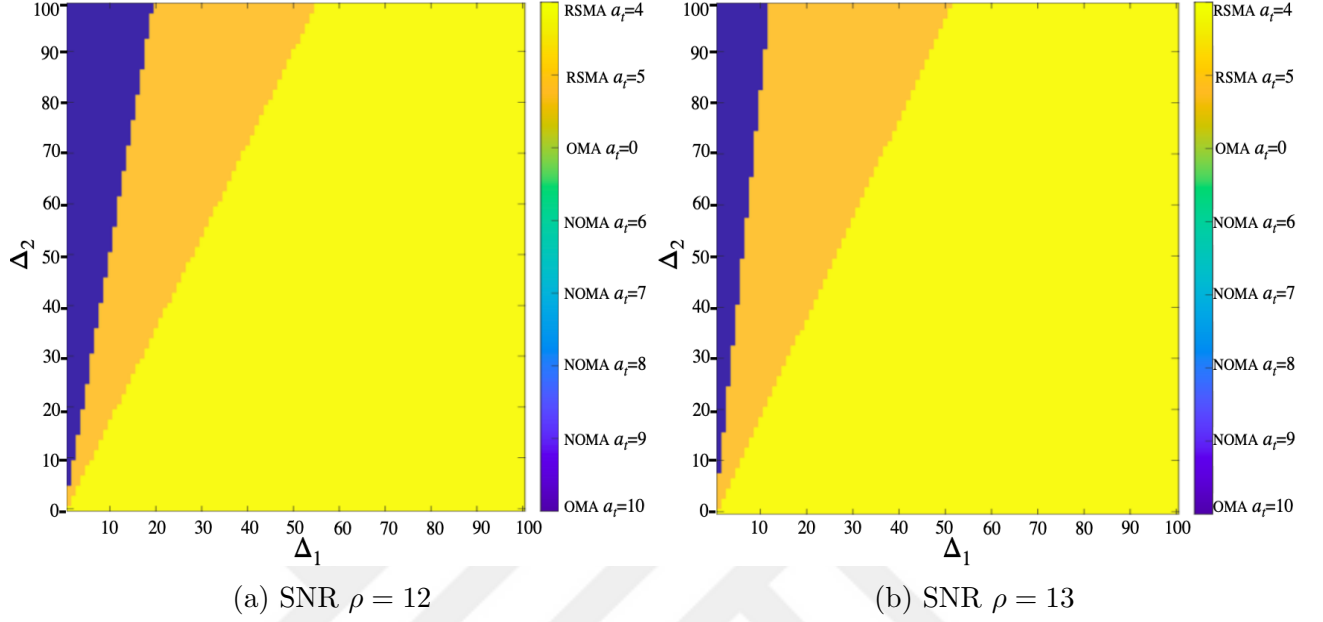


Figure 5.14: Adaptive policy with unequal target rates and user weights $[(R_1^* = 0.8, R_2^* = 1.0), (w_1 = 0.3, w_2 = 0.7), (R_{c,1}^* = R_{c,2}^* = 0.2)]$

5.3.3 Impact of Common Target Rates on Adaptive Policy

An increase in the common target rate yields to a decrease in WSAoI since increasing common target rate increases probability of RSMA scheme selection for which BS serves both users together. However, serving both users together increases the age difference of the users, which in turn requires selection of also OMA scheme. RSMA scheme selection increases, and OMA scheme selection decreases with increasing SNR. Increase of common target rate is more effective on reducing WSAoI when $w_1 > w_2$ than $w_1 < w_2$. WSAoI is comparatively very small when $w_1 < w_2$ than $w_1 > w_2$. Decreasing private part of user rate is more effective on the performance metric when the common part of the user rate is maximized.

5.3.4 Impact of Private Target Rates on Adaptive Policy

A decrease in the private target rate yields to a decrease in WSAoI since decreasing private target rate increases common target rate and probability of RSMA scheme selection for which BS serves both users together. However, serving both users together increases the age difference of the users, which in turn requires selection of also OMA scheme. RSMA scheme selection increases, and OMA scheme selection decreases with increasing SNR. At high private target rates, NOMA scheme is preferred by BS to RSMA. Decrease of private target rate is more effective on reducing WSAoI when $w_1 > w_2$ than $w_1 < w_2$. WSAoI is comparatively small when $w_1 < w_2$ than $w_1 > w_2$. Decreasing private part of user rate is more effective on the performance metric when the private part of the user rate is minimized.

5.4 Age-Energy Tradeoff

In this scenario, transmission SNR and user distance to BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant. The analysis are done under equal target rates (with equal and unequal user weight cases) and unequal target rates (with equal and unequal user weights cases). For each case, three different sub-scenarios are analysed:

- The user distances are changed while keeping the user distance ratio ($d_2/d_1 = 2$) constant,
- User 1's distance (d_1) is changed while keeping user 2's distance (d_2) constant,
- User 2's (d_2) distance is changed while keeping user 1's (d_1) distance constant.

Table 5.19: Simulation parameters for Age-Energy Tradeoff under equal target rates and user weights

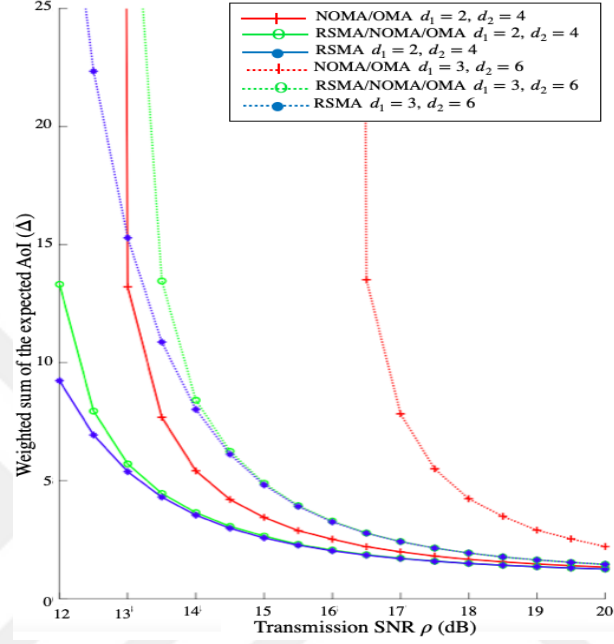
Parameter	Value
R_1^*, R_2^*	1
w_1, w_2	0.5
d_1, d_2	(2,4), (3,4), (2,6), (3,6)
N	10
ρ in dB	[12, 12.5, ..., 20]
$\lambda_{c1} = \lambda_{c2}$	0.13, 0.14, 0.15, 0.16, 0.17, 0.18, 0.19

5.4.1 Age-Energy Tradeoff Under Equal Target Rates and Equal User Weights

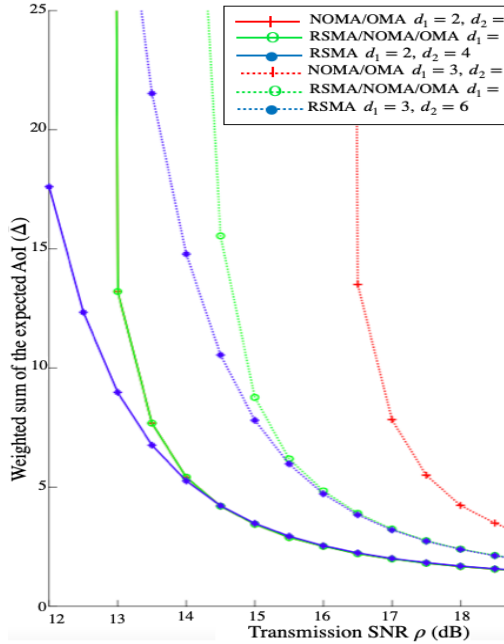
Adaptive policy is investigated under different values for transmission SNR ρ and distances of user 1 and 2 from BS, d_1 and d_2 . This is an age-energy trade-off study. Simulation parameters and results of the simulations for age-energy trade-off for the first sub-scenario where d_2/d_1 is constant are given in Table 5.19 and Figure 5.15. Figure 5.15 illustrates simulation results for $\lambda_{c,1} = \lambda_{c,2} = 0.18, 0.15, 0.12$ for both user distances to the BS. Results for other λ_c values are given in Appendix D.1.

The simulation results for the second and third sub-scenarios, user 1's or user 2's distance is changed while keeping user 2's or user 1's distance constant, are given in Figure 5.16 and Figure 5.17. Both figures imply that increasing one user's distance while keeping the other's distance the same increases WSAoI, and the adaptive policy outperforms NOMA/OMA in all cases.

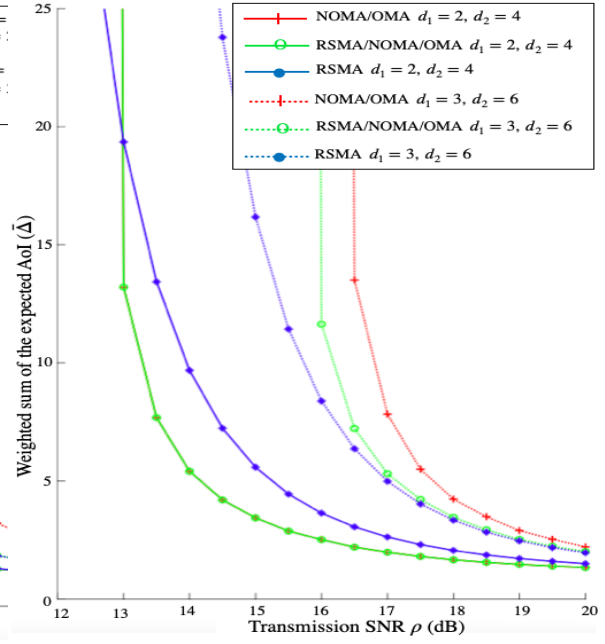
It is concluded from Figure 5.15 that RSMA outperforms NOMA/OMA schemes, in terms of WSAoI, at λ_c values above a threshold value of 0.12, for all transmission SNR values. Being able to service to both users together yields to less WSAoI than servicing to only one user at a time. BS allocates more power to far user. When the user distances are not high, e.g. $d_1 = 2, d_2 = 4$, BS can serve both users together at high SNR values, and selects either RSMA or NOMA. Serving both users together decreases WSAoI. If λ_c is above a certain value, which decreases with increasing user distance to BS, RSMA takes



(a) $d_2/d_1 = 2$ [$\lambda_c = 0.18$]



(b) $d_2/d_1 = 2$ [$\lambda_c = 0.15$]



(c) $d_2/d_1 = 2$ [$\lambda_c = 0.12$]

Figure 5.15: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [equal target rates and user weights]

precedence over NOMA. However, serving both users together may increase the age difference of the users and outage probability of the user in worse condition, which in turn is decreased by selecting OMA scheme. RSMA scheme is not selected at small values of λ_c as shown in Figure 5.15(c) for the small user distances ($d_1 = 2, d_2 = 4$), for which NOMA dominates and OMA scheme is selected for the user with high outage probability. However, RSMA selection dominates over NOMA/OMA at higher user distances ($d_1 = 3, d_2 = 6$) even at small λ_c values (e.g. $\lambda_{c,1} = \lambda_{c,2} = 0.12$). For the user distances $d_1 = 3, d_2 = 6$, outage probability of especially the far user may increase. To avoid this, more power is tried to be allocated to the far user so that the age difference between the users will be less, which allows the BS to serve both users together at high SNR values. The advantage of RSMA scheme selection in terms of WSAoI is very obvious at low SNR values. For example, WSAoI with RSMA scheme is about one third of the age with NOMA/OMA schemes. A policy seeking a good age-energy tradeoff could involve the RSMA mode. The effect of user distance on WSAoI is comparatively high at low SNR values. All the curves except NOMA/OMA for $d_1 = 3, d_2 = 6$ seem to converge to the same value of WSAoI when SNR=20 dB. NOMA/OMA schemes seem to be disadvantageous for the user at distances further to BS.

Figure 5.15(a) and Figure 5.17 show that for a selected SNR (e.g. 13), WSAoI values are 5.2, 7.5, 10.2, and 15.4 for the user distances of ($d_1 = 2, d_2 = 4$), ($d_1 = 3, d_2 = 4$), ($d_1 = 2, d_2 = 6$) and ($d_1 = 3, d_2 = 6$), respectively, when RSMA is used. The increase in WSAoI is substantially higher when NOMA/OMA is used. SNR values of 13, 13.5, 14 and 15 dB seem to be good tradeoff values for the user distances of ($d_1 = 2, d_2 = 4$), ($d_1 = 3, d_2 = 4$), ($d_1 = 2, d_2 = 6$) and ($d_1 = 3, d_2 = 6$), respectively.

Figure 5.15 shows that increasing transmission SNR ρ decreases WSAoI at a cost of increasing power consumption. Thanks to the adaptive RSMA scheme that outperforms the NOMA/OMA scheme, in turn results in substantial reduction of transmission power. For example, in Figure 5.15(a), when WSAoI is equal to 5.4, by using the adaptive RSMA/NOMA/OMA scheme instead of NOMA/OMA scheme, at the user distances ($d_1 = 2, d_2 = 4$), transmission SNR ρ is decreased from 14 dB to 13 dB, which corresponds to 20.6% decrease in power consumption.

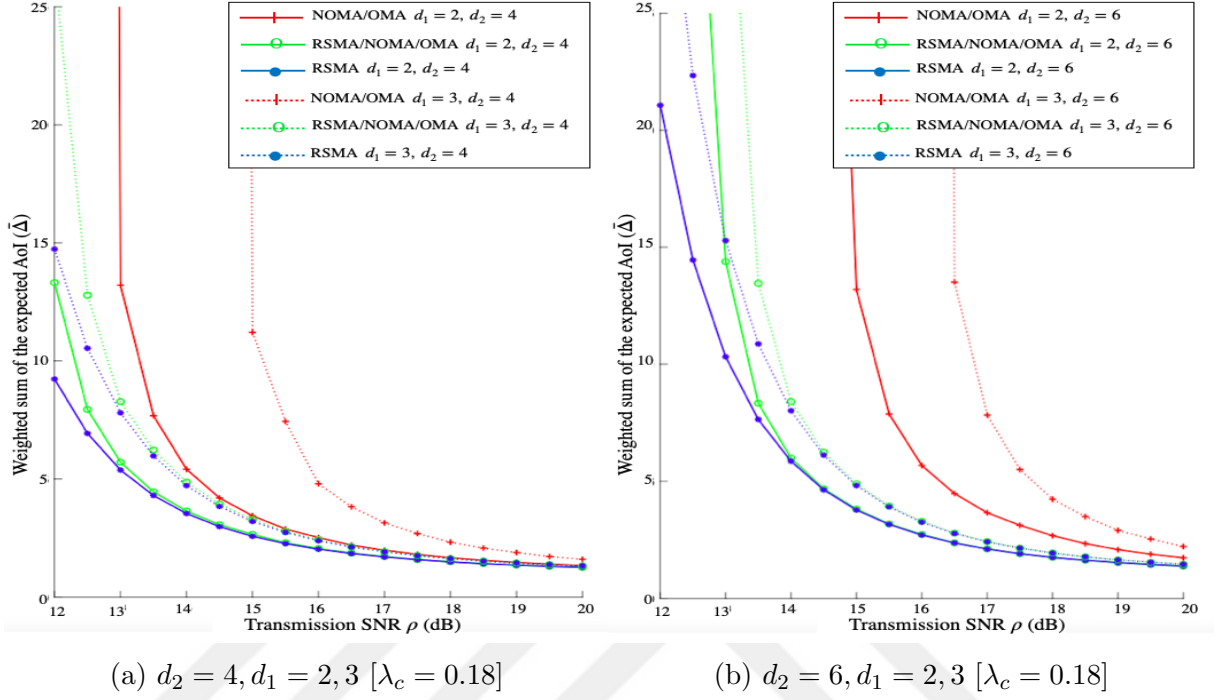


Figure 5.16: Age-energy tradeoff for user distances $d_2 = \text{constant}$, d_1 is changed [equal target rates and user weights]

Save of energy is higher for the user distances of $(d_1 = 3, d_2 = 6)$. Slope of WSAoI - transmission SNR curve decreases as the transmission SNR increases, and becomes horizontal at about SNR = 20. Age-energy trade-off could be made at about SNR = 16 – 18.

Comparing Figure 5.15(a) with Figure 5.15(b) implies an increase in λ_c yields to a decrease in WSAoI. For the selected same age, it yields to 20.6% decrease in power consumption for RSMA scheme.

Figure 5.16 and Figure 5.17 show that effect of user distances on WSAoI is low at high SNR values, while very noticeable at low SNR values. At high SNR values, BS can serve both users together, which reduces WSAoI. However, the reduction in WSAoI is low at high SNR values. For example, WSAoI for the RSMA scheme at user distances $d_1 = 2, d_2 = 6$ is about two times of WSAoI at the user distances $d_1 = 2, d_2 = 4$.

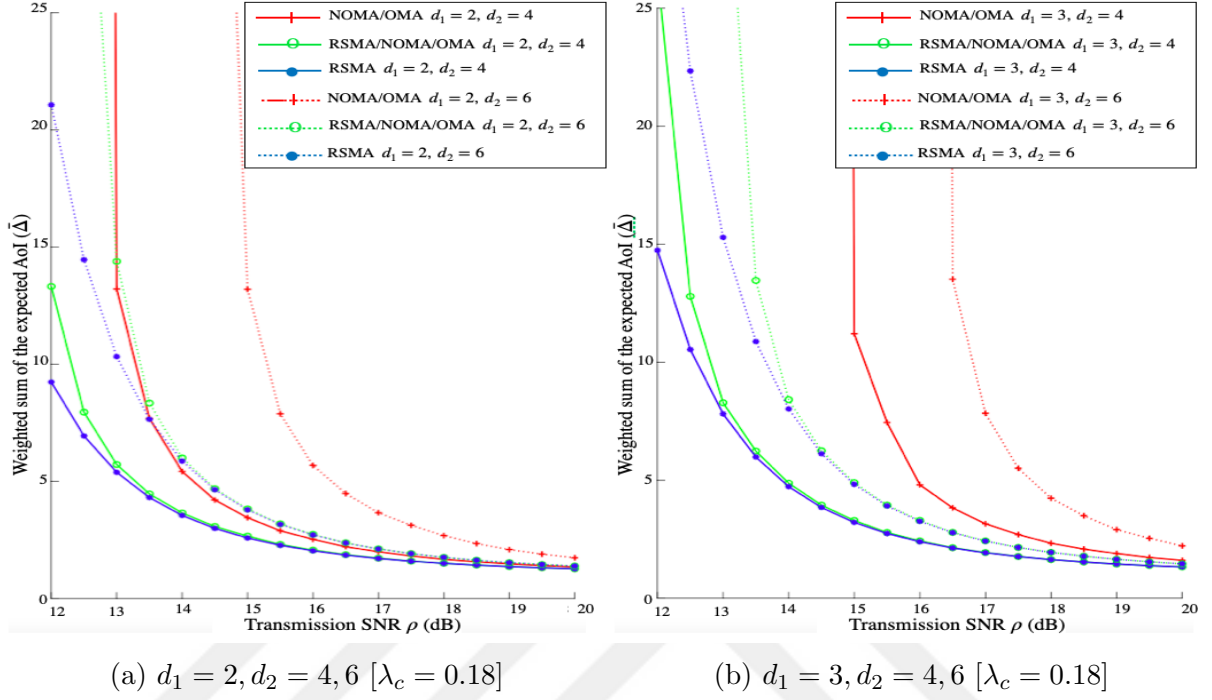


Figure 5.17: Age-energy tradeoff for user distances $d_1 = \text{constant}$, d_2 is changed [equal target rates and user weights]

5.4.2 Age-Energy Tradeoff Under Equal Target Rates and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied under equal target rates and unequal user weight cases, while keeping values of all other parameters as constant.

Table 5.20: Simulation parameters for impact of unequal user weight distribution on Age-Energy Tradeoff

Parameter	Value
R_1^*, R_2^*	1
$R_{c,1}^*, R_{c,2}^*$	(0.15, 0.15)
w_1, w_2	(0.3, 0.7), (0.7, 0.3)
(d_1, d_2)	(2, 4), (3, 6), (3, 4), (2, 6)
N	10
SNR ρ in dB	[12, 12.5, ..., 20] dB

Age-energy tradeoff under equal target rates is investigated for different values for distances of user 1 and 2 from BS. Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are given in the Table 5.20, and in Figure 5.18(a), Figure 5.18(b) for $w_1 > w_2$ [$\lambda = 0.15, \lambda = 0.18$], and in the Figure 5.19(a), Figure 5.19(b) for $w_2 > w_1$ [$\lambda = 0.15, \lambda = 0.18$], respectively.

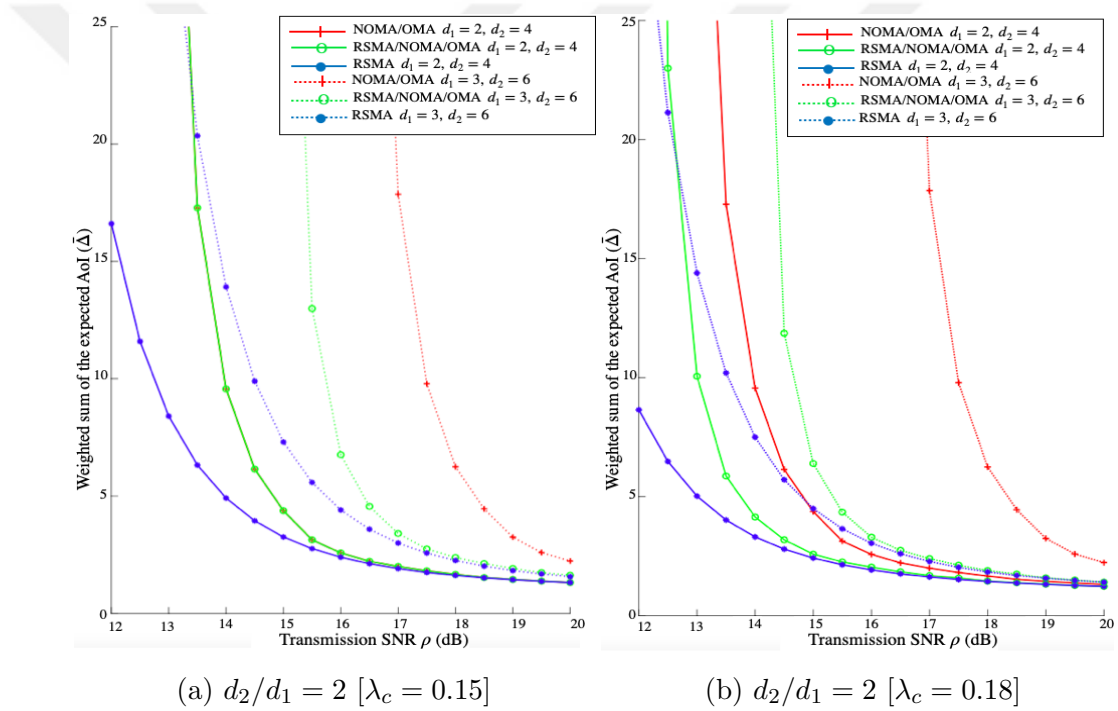


Figure 5.18: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [equal target rates, ($w_1 = 0.7, w_2 = 0.3$)]

Figure 5.18(a) and Figure 5.18(b) show that RSMA policy outperforms NOMA/OMA policy for both $w_1 > w_2$ and $w_2 > w_1$ for both user distances and at all ranges of SNR (ρ) (0.12 - 0.20).

Comparison of Figure 5.18(a) with Figure 5.18(b) for $w_1 > w_2$, and Figure 5.19(a) with Figure 5.19(b) for $w_2 > w_1$ show that an increase in λ_c yields to a decrease in WSAoI. This effect increases with decreasing transmission SNR values. It is clear from the figures that RSMA is the best candidate in terms of power consumption in comparison to NOMA and OMA schemes, for λ_c which is

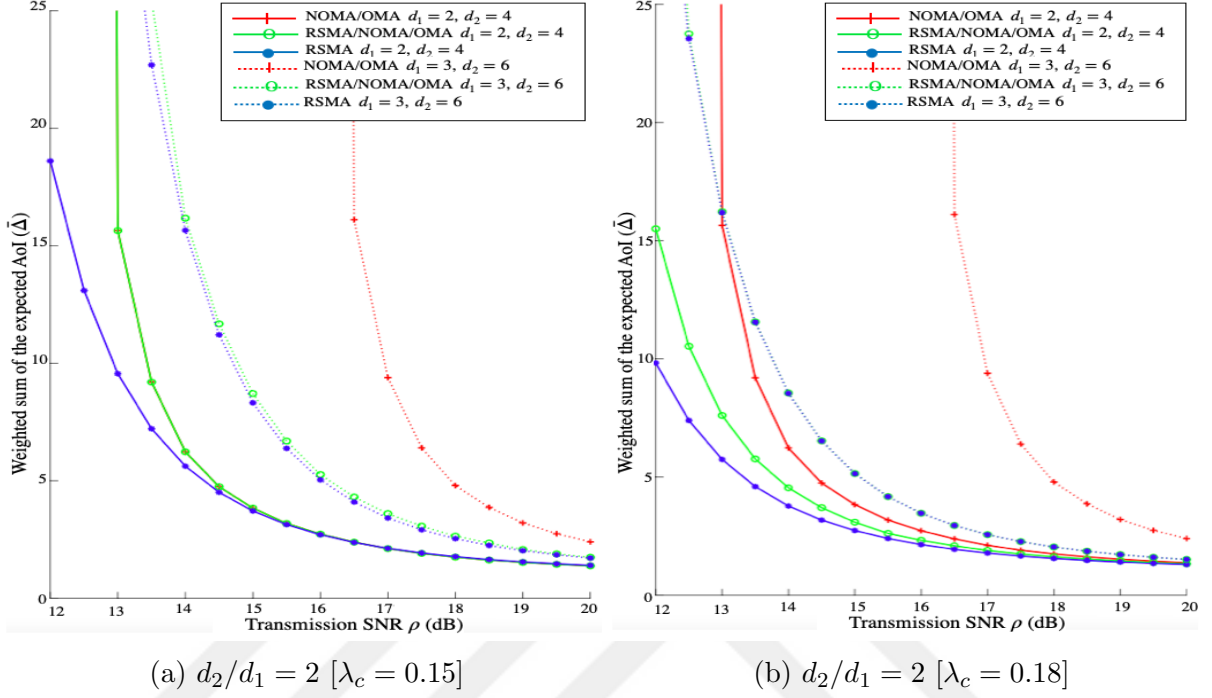


Figure 5.19: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [equal target rates, $(w_1 = 0.3, w_2 = 0.7)$]

above a certain value, and this value decreases with increasing user distances.

Figure 5.18 and Figure 5.19 show that increasing the user distances from BS increases WSAoI, and this impact is higher when $w_1 < w_2$ than $w_1 > w_2$. Increasing weight of the far user decreases its outage probability, and allows BS to serve both users simultaneously, which in turn reduces WSAoI. Effect of the user distances on WSAoI decreases with increasing transmission SNR ρ , since at high values of SNR, both users can be served together at also high user distances, and outage probability of the users might change slightly with increase of SNR, which may yield to a small change in WSAoI.

The simulation results for the second and third sub-scenarios, where user 1's or user 2's distance is changed while keeping user 2's or user 1's distance constant, are given in Figure 5.20 and Figure 5.21 for $(w_1 > w_2)$ in Figure 5.22 and Figure 5.23 for $(w_2 > w_1)$, respectively. All figures imply that increasing one user's distance while keeping the other's distance the same increases WSAoI, and the adaptive policy outperforms NOMA/OMA in all cases.

Figures 5.21 and Figure 5.23 show that for a selected SNR (e.g. 13), WSAoI values are (5,9), (7.5,14.8), (5.4,12) and (8,16.5) for the user distance, target rate and user weight combinations, respectively for the related figures, when RSMA scheme is used. The increase in WSAoI is substantially higher when NOMA/OMA scheme is used. SNR values of (13,14), (13.5,14.5), (13.2,14.4) and (13.6,15) seem to be good tradeoff values for the user distances of $(d_1 = 2, d_2 = 4)$, $(d_1 = 3, d_2 = 4)$, $(d_1 = 2, d_2 = 6)$ and $(d_1 = 3, d_2 = 6)$, respectively for the related figures.

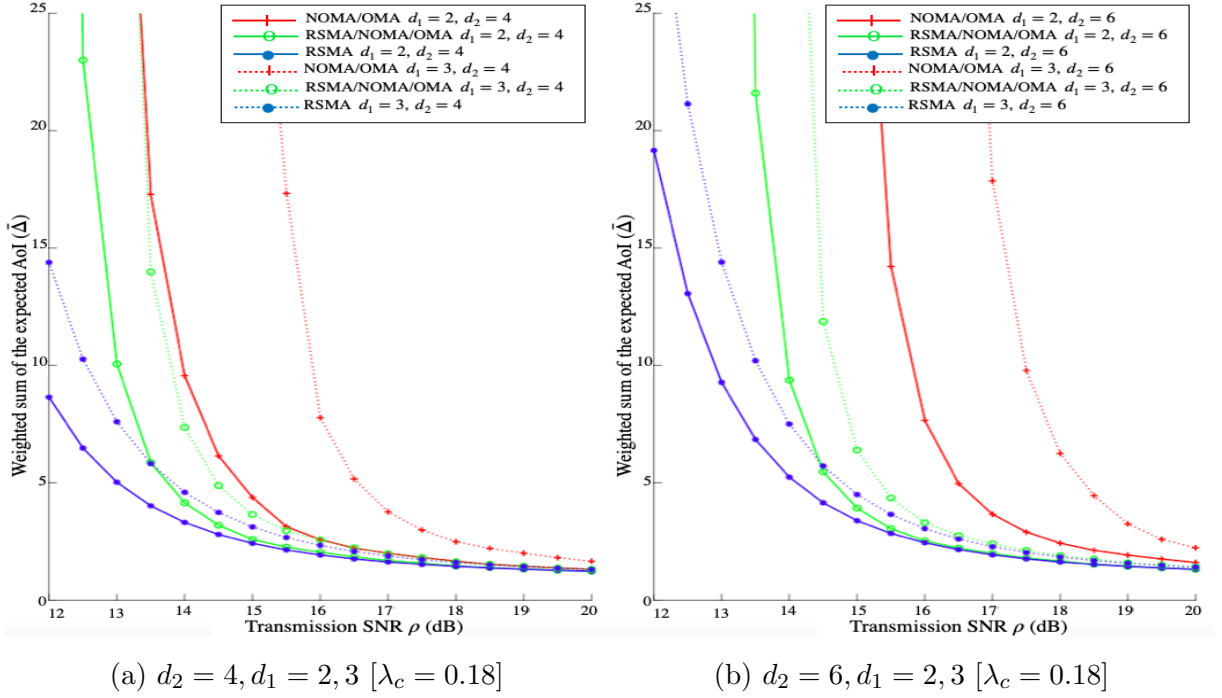
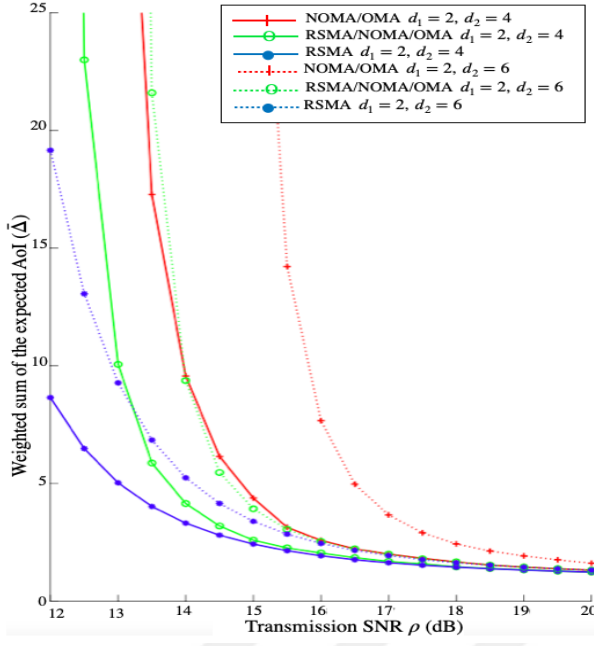


Figure 5.20: Age-energy tradeoff for user distances $d_2 = \text{constant}$, d_1 is changed [equal target rates, $(w_1 = 0.7, w_2 = 0.3)$]

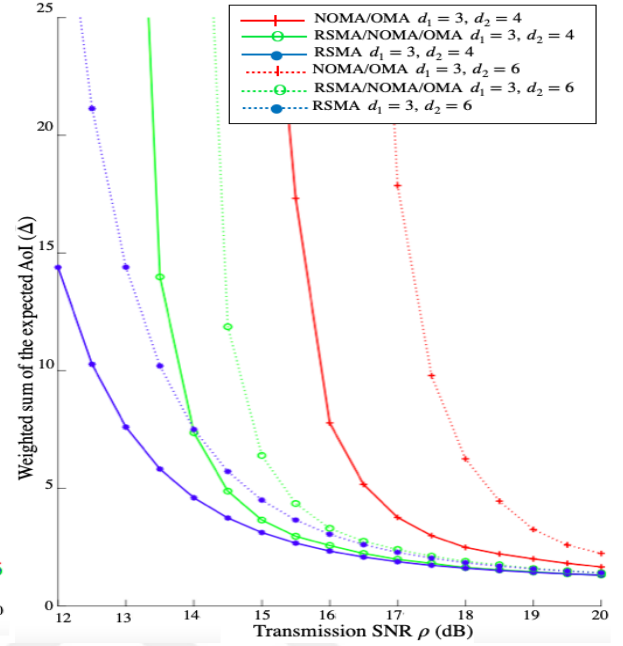
5.4.3 Age-Energy Tradeoff Under Unequal Target Rates and Equal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under unequal target rates is investigated for different

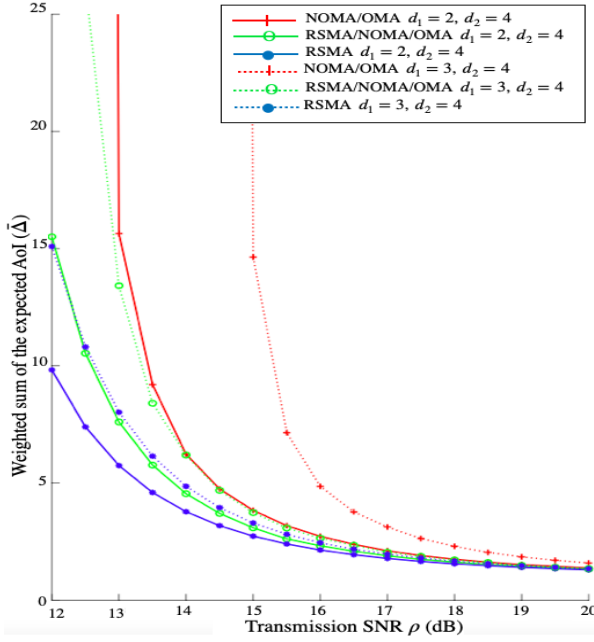


(a) $d_1 = 2, d_2 = 4, 6$ [$\lambda_c = 0.18$]

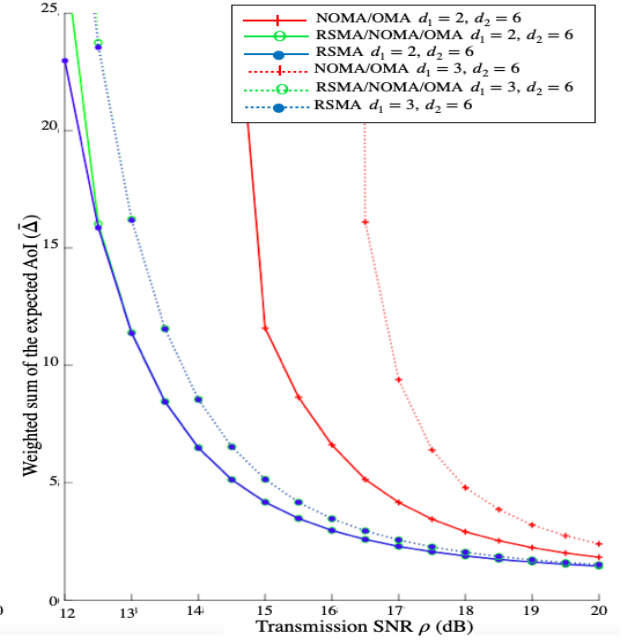


(b) $d_1 = 3, d_2 = 4, 6$ [$\lambda_c = 0.18$]

Figure 5.21: Age-energy tradeoff for user distances $d_1 = \text{constant}$, d_2 is changed [equal target rates, ($w_1 = 0.7, w_2 = 0.3$)]



(a) $d_2 = 4, d_1 = 2, 3$ [$\lambda_c = 0.18$]



(b) $d_2 = 6, d_1 = 2, 3$ [$\lambda_c = 0.18$]

Figure 5.22: Age-energy tradeoff for user distances $d_2 = \text{constant}$, d_1 is changed [equal target rates, ($w_1 = 0.3, w_2 = 0.7$)]

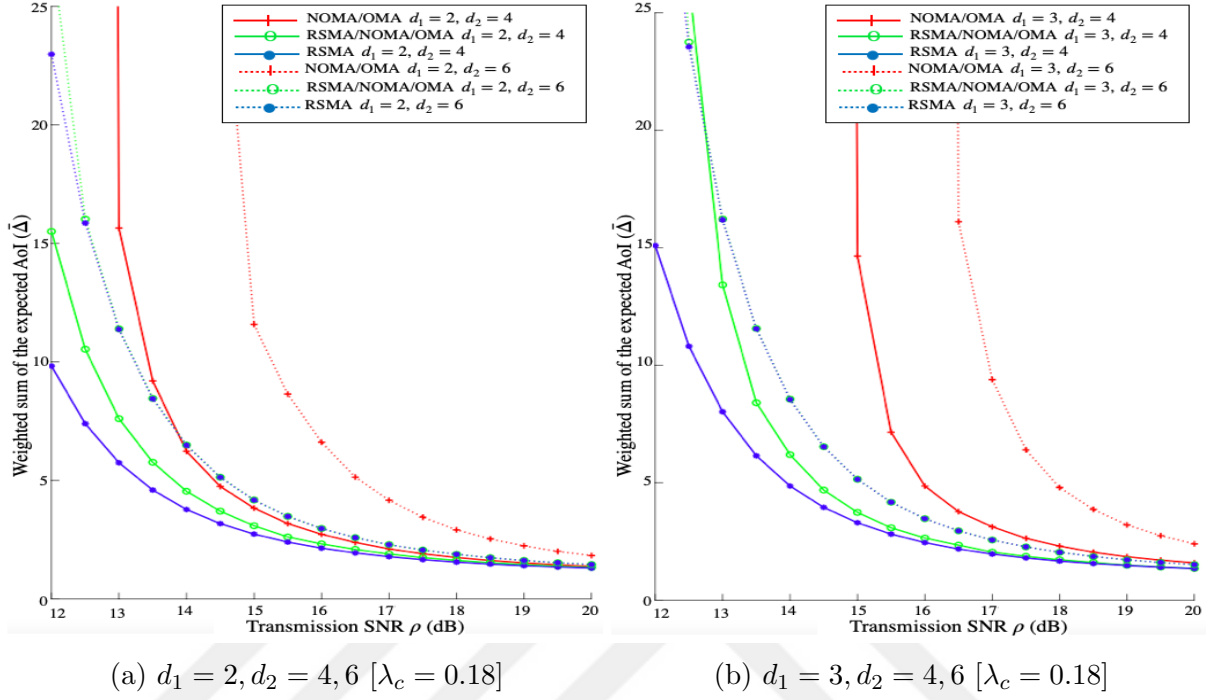


Figure 5.23: Age-energy tradeoff for user distances $d_1 = \text{constant}$, d_2 is changed [equal target rates, $(w_1 = 0.3, w_2 = 0.7)$]

values for distances of useruser from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the all sub-scenarios under equal user weight distribution are shown in the Table 5.21, and in Figure 5.24 for $R_1^* > R_2^*$ and in Figure 5.25 for $R_2^* > R_1^*$.

Figure 5.24 and Figure 5.25 show that RSMA scheme outperforms NOMA/OMA schemes for both $R_1^* > R_2^*$ and $R_2^* > R_1^*$, for all user distances, and at all ranges of SNR (ρ) (0.12 - 0.20). Both figures also show that increasing either user's distance increases WSAoI. Increasing far user's distance is more effective on WSAoI than increasing near user's distance.

A comparison of Figure 5.24 and Figure 5.25 implies that, under same conditions, WSAoI is higher for $R_2^* > R_1^*$ than for $R_1^* > R_2^*$.

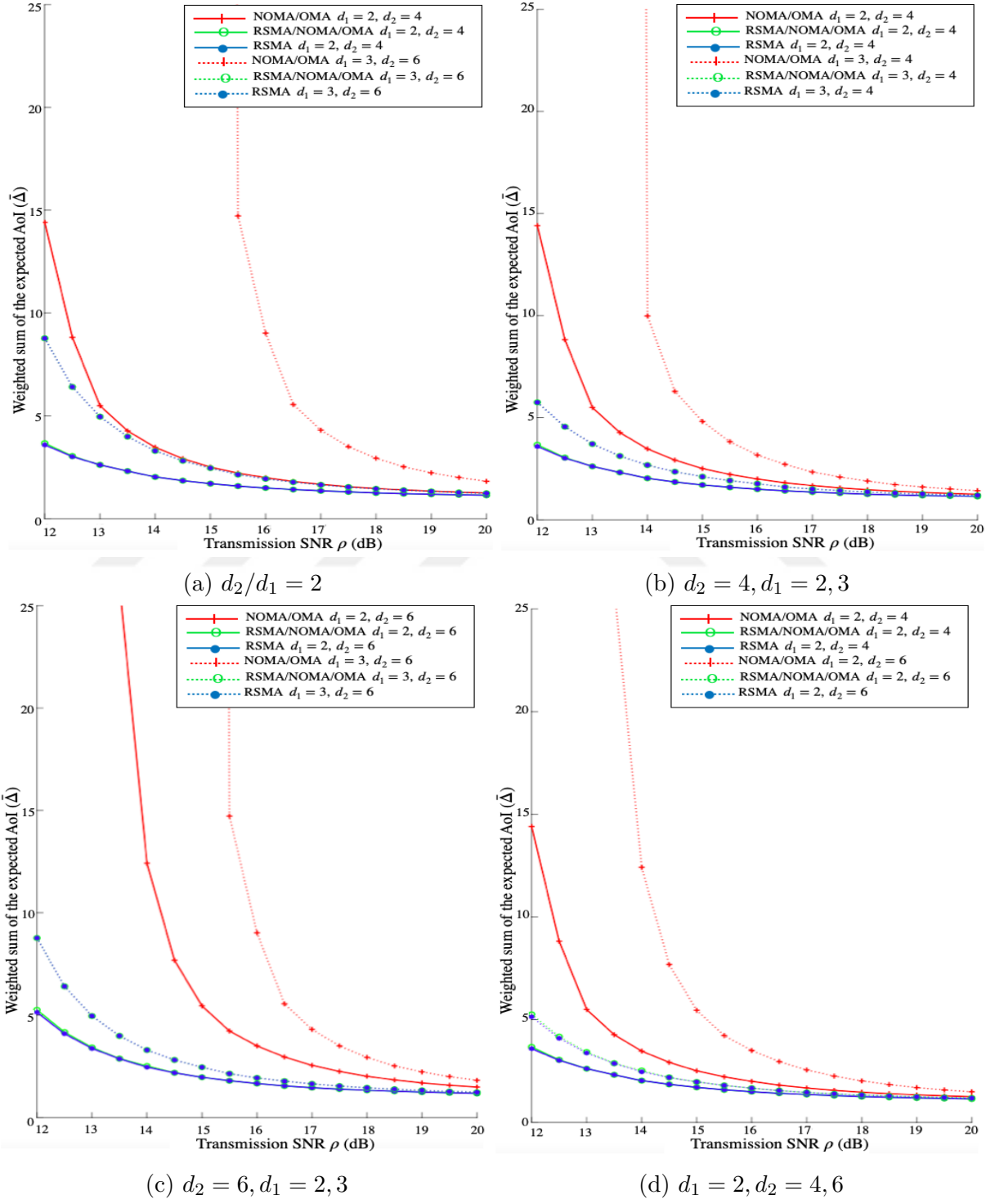


Figure 5.24: Age-energy tradeoff for different user distance cases when $w_1 = w_2 = 0.5$, $\lambda_{c,1} = \lambda_{c,2} = 0.18$ [$R_1^* = 1.0, R_2^* = 0.8$]

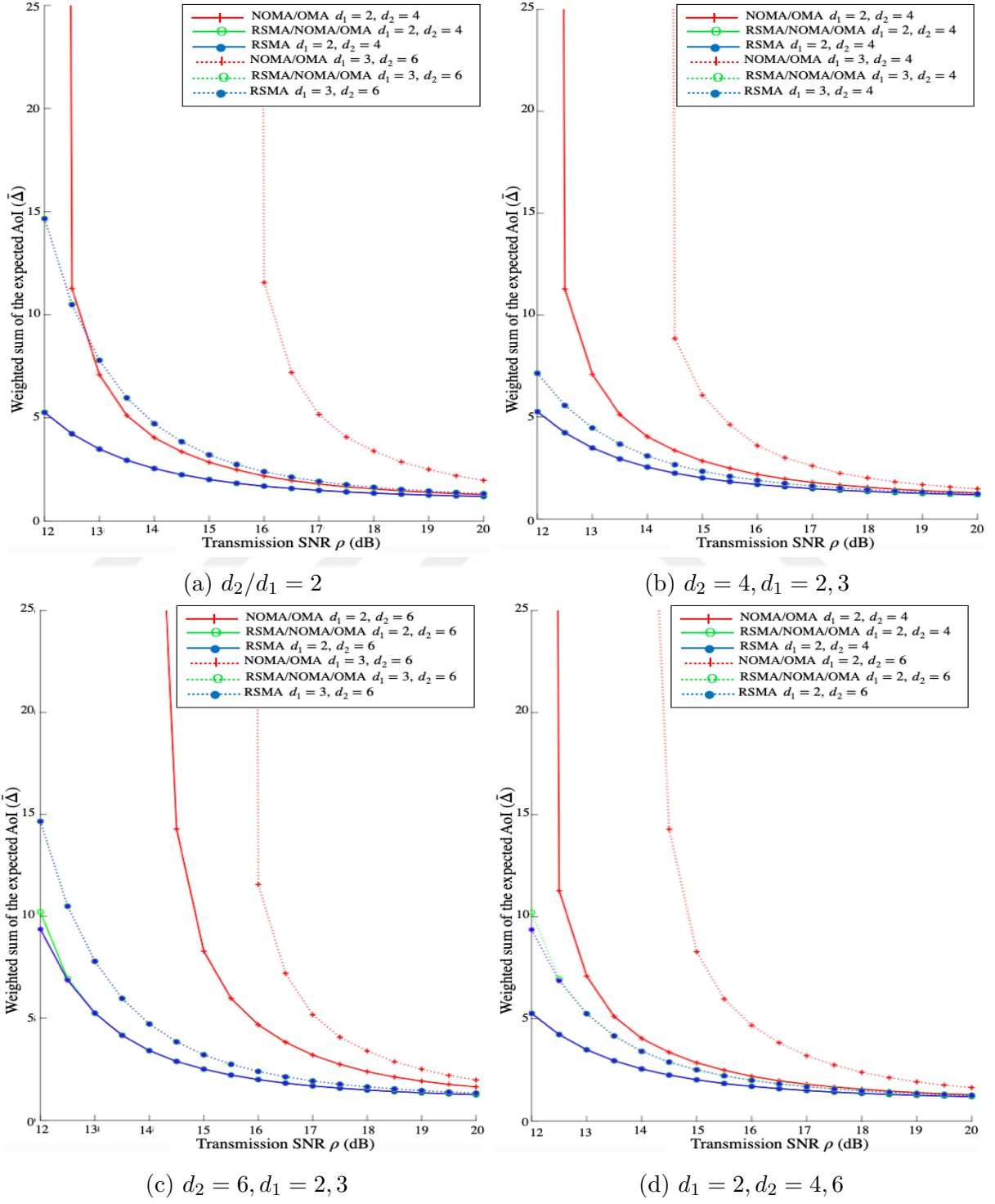


Figure 5.25: Age-energy tradeoff for different user distance cases when $w_1 = w_2 = 0.5$ [$(R_2^* = 1.0) > (R_1^* = 0.8)$]

Table 5.21: Simulation parameters for unequal target rates and equal user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$\lambda_{c,1} = \lambda_{c,2}$	0.18
w_1, w_2	(0.5,0.5)
N	10
ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (2,6), (3,4), (3,6)

Table 5.22: Simulation parameters for unequal target rates and user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$\lambda_{c,1} = \lambda_{c,2}$	0.18
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (2,6), (3,4), (3,6)

5.4.4 Age-Energy Tradeoff Under Unequal Target Rates and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under unequal target rates is investigated for different values for distances of users, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are shown in the Table 5.22, and in Figure 5.26 for $R_1^* > R_2^*$, $\{[w_1 > w_2], [w_2 > w_1]\}$ and in Figure 5.27 for $R_2^* > R_1^*$, $\{[w_1 > w_2], [w_2 > w_1]\}$.

Figure 5.26 and Figure 5.27 show that RSMA scheme outperforms NOMA/OMA schemes for $R_1^* > R_2^*$ and $R_2^* > R_1^*$, for both user distances and at all ranges of SNR (ρ) (0.12 - 0.20).

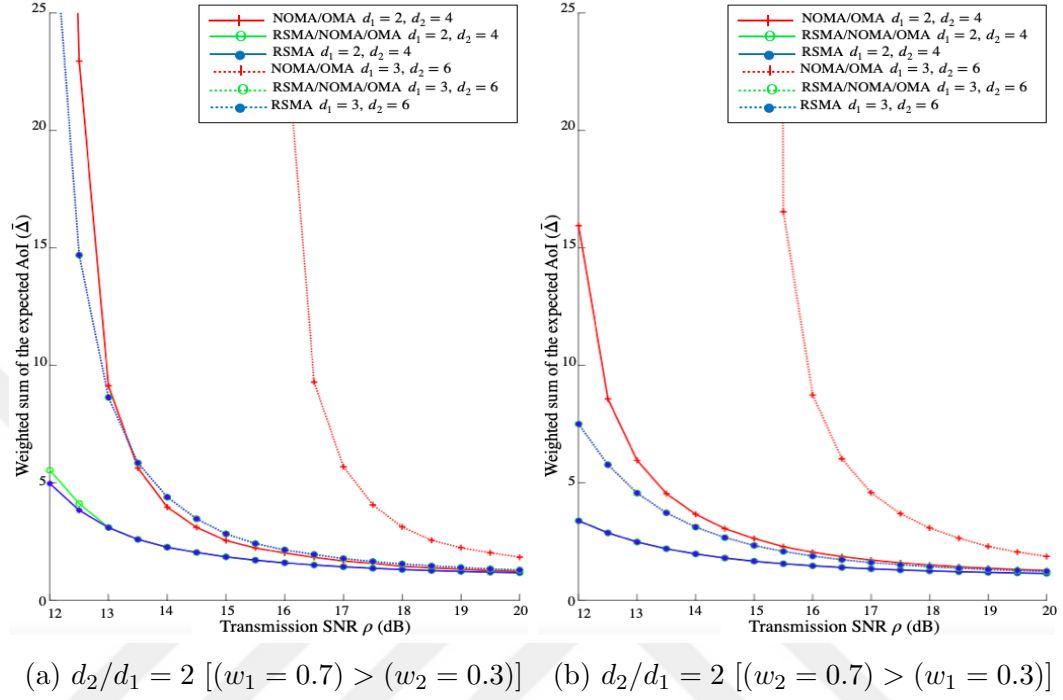
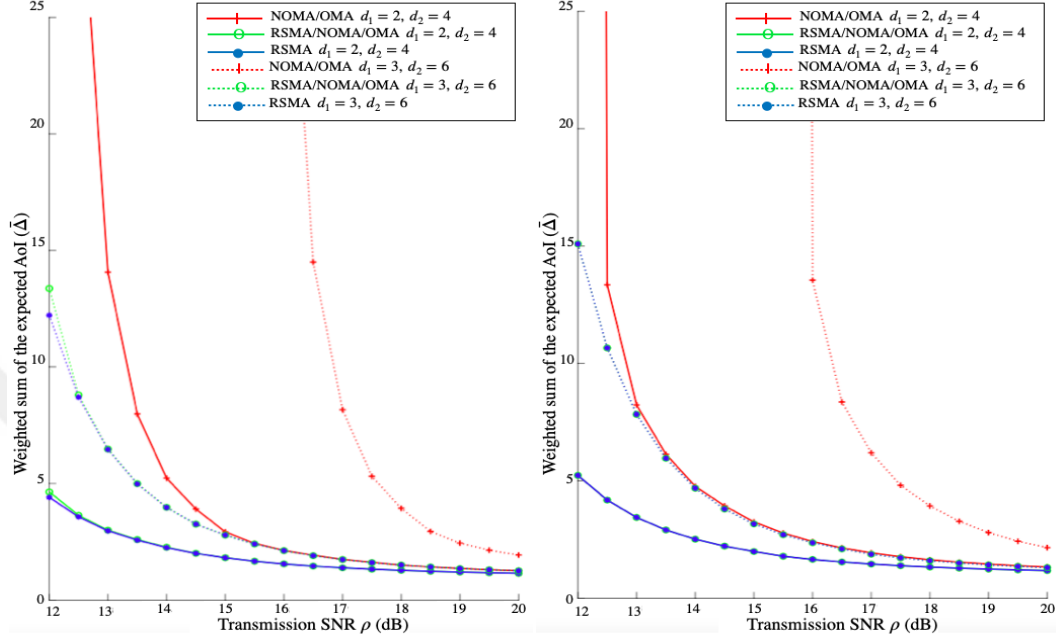


Figure 5.26: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [$R_1^* = 1.0, R_2^* = 0.8$]

Figure 5.26 shows that decreasing weight of the user with higher rate decreases WSAoI substantially. As expected, increasing the user distances increases WSAoI. However, this observation is much obvious at low SNRs for both users, and especially at user with higher rate.

Comparison of Figure 5.26(a) with Figure 5.26(b) for $R_1^* > R_2^*$, shows that the decrease in w_1 , decreases WSAoI. This effect increases with decreasing transmission SNR values. The adaptive policy RSMA/ NOMA/ OMA converges to RSMA policy and it favors RSMA mode more when w_1 is decreased. It is clear from the figures that RSMA is the best candidate in terms of power consumption in comparison to NOMA and OMA schemes.

Figure 5.27 shows that decreasing the weight of the user with higher rate decreases WSAoI, however this effect is not as obvious as in Figure 5.26. As expected, increasing the user distances increases WSAoI. However, this observation is much obvious at the low SNRs for both users, and especially at user with higher rate.



(a) $d_2/d_1 = 2$ [$(w_1 = 0.7) > (w_2 = 0.3)$] (b) $d_2/d_1 = 2$ [$(w_2 = 0.7) > (w_1 = 0.3)$]

Figure 5.27: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [$R_1^* = 0.8$, $R_2^* = 1.0$]

Comparison of Figure 5.27(a) with Figure 5.27(b) for $R_2^* > R_1^*$, shows that the decrease in w_2 , decreases WSAoI. This effect increases with decreasing transmission SNR values. The adaptive policy RSMA/ NOMA/ OMA converges to RSMA policy and it favors RSMA mode more when w_1 is decreased. It is clear from the figures that RSMA is the best candidate in terms of power consumption in comparison to NOMA and OMA schemes.

Comparing Figure 5.26 with 5.27 shows that decreasing rate of closer user while increasing rate of further user decreases WSAoI when the weight of the near user is higher, but increases WSAoI when the weight of the further user is higher.

Considering Figure 5.26 and Figure 5.27 together, it can be concluded that decreasing the user weight of the user with higher target rate conditions decreases WSAoI.

Figure 5.26 and Figure 5.27 show that increasing the user distances from BS

increases WSAoI, and this impact is higher when $R_2^* > R_1^*$ than $R_1^* > R_2^*$. Effect of user distances on WSAoI decreases with increasing transmission SNR ρ .

The simulation results for the second and third sub-scenarios, where user 1's or user 2's distance is changed while keeping user 2's or user 1's distance constant, are given in Figure 5.28 and Figure 5.29 for $R_1^* > R_2^*$ ($w_1 > w_2, w_2 > w_1$) in Figure 5.30 and Figure 5.31 for $R_2^* > R_1^*$ ($w_1 > w_2, w_2 > w_1$), respectively. All figures show that increasing the one user's distance while keeping the other's distance the same increases WSAoI, and the adaptive policy outperforms NOMA/OMA in all cases. RSMA scheme outperforms NOMA/OMA schemes for all cases at all user distances, weights, and transmission SNR values.

Figure 5.28(a) shows that increasing user 1's distance from $d_1 = 2$ to $d_1 = 3$ under $w_1 > w_2$ while keeping user 2's distance constant ($d_2 = 4$) under $\rho = 13$ dB for RSMA increases WSAoI by 65%. This increase is comparatively higher when user 2's distance is kept at $d_2 = 6$. Comparing Figure 5.28(a) with Figure 5.28(c), it is concluded that decreasing closer user's distance from $d_1 = 3$ to $d_1 = 2$ is more effective on reducing WSAoI when the further user is at $d_2 = 6$ than at $d_2 = 4$.

Figure 5.28(b) shows that increasing user 1's distance from $d_1 = 2$ to $d_1 = 3$ under $w_2 > w_1$ while keeping user 2's distance constant ($d_2 = 4$) under $\rho = 13$ dB for RSMA increases WSAoI by 32%. This increase is comparatively higher when user 2's distance is kept at $d_2 = 6$. Comparing Figure 5.28(b) with Figure 5.28(d), it is concluded that decreasing closer user's distance from $d_1 = 3$ to $d_1 = 2$ is more effective on reducing WSAoI when the further user is at $d_2 = 6$ than at $d_2 = 4$.

A comparison of Figure 5.28(a) with 5.28(b), and Figure 5.28(c) with 5.28(d) shows effect of the user weight on WSAoI. It can be concluded from the comparisons that increasing the weight of the user with lower rate decreases WSAoI, when $R_1^* > R_2^*$. This effect seems to be higher when the far user's distance is higher.

Figure 5.29(a) shows that increasing user 2's distance from $d_2 = 4$ to $d_2 = 6$ under $w_1 > w_2$ while keeping user 1's distance constant ($d_1 = 2$) under $\rho = 13$ dB for RSMA increases WSAoI by 35.3%. This increase is comparatively higher when user 1's distance is kept at $d_1 = 3$. Comparing Figure 5.29(a) with Figure 5.29(c), it can be concluded that decreasing the far user's distance from $d_2 = 6$ to $d_2 = 4$ is more effective on reducing WSAoI when the near user is at $d_1 = 3$ than at $d_1 = 2$.

Figure 5.29(b) shows that increasing user 2's distance from $d_2 = 4$ to $d_2 = 6$ under $w_2 > w_1$ while keeping user 1's distance constant ($d_1 = 2$) under $\rho = 13$ dB for RSMA increases WSAoI by 36%. This increase is comparatively higher when user 1's distance is kept at $d_1 = 3$. Comparing Figure 5.29(b) with Figure 5.29(d), it is concluded that decreasing the far user's distance from $d_2 = 6$ to $d_2 = 4$ is more effective on reducing WSAoI when the rear user is at $d_1 = 3$ than at $d_1 = 2$.

A comparison of Figure 5.29(a) with 5.29(b), and Figure 5.29(c) with 5.29(d) shows effect of the user weight on WSAoI. It can be concluded from the comparisons that increasing the weight of the user with lower rate decreases WSAoI, when $R_1^* > R_2^*$. This effect seems to be higher when the near user's distance is higher.

Figure 5.30(a) shows that increasing user 1's distance from $d_1 = 2$ to $d_1 = 3$ under $w_2 > w_1$ while keeping user 2's distance constant ($d_2 = 4$) under $\rho = 13$ dB for RSMA increases WSAoI by 52.4%. This increase is comparatively higher when user 2's distance is kept at $d_2 = 6$. Comparing Figure 5.30(a) with Figure 5.30(c), it can be concluded that decreasing the closer user's distance from $d_1 = 3$ to $d_1 = 2$ is more effective on reducing WSAoI when the further user is at $d_2 = 6$ than at $d_2 = 4$.

Figure 5.30(b) shows that increasing user 1's distance from $d_1 = 2$ to $d_1 = 3$ under $w_1 > w_2$ while keeping user 2's distance constant ($d_2 = 4$) under $\rho = 13$ dB for RSMA increases WSAoI by 22.2%. This increase is comparatively higher when user 2's distance is kept at $d_2 = 6$. Comparing Figure 5.30(b) with Figure

5.30(d), it is concluded that decreasing the closer user's distance from $d_1 = 3$ to $d_1 = 2$ is more effective on reducing WSAoI when the further user is at $d_2 = 6$ than at $d_2 = 4$.

A comparison of Figure 5.30(a) with 5.30(b), and Figure 5.28(c) with 5.30(d) shows effect of the user weight on WSAoI. It can be concluded from the comparisons that increasing the weight of the user with lower rate decreases WSAoI, when $R_2^* > R_1^*$. However, when the distance of far user (d_2) is very high like the case in Figure 5.30(c) and Figure 5.30(d), effect is in opposite direction.

Figure 5.31(a) indicates that increasing user 2's distance from $d_2 = 4$ to $d_2 = 6$ under $w_1 > w_2$ while keeping user 1's distance constant ($d_1 = 2$) under $\rho = 13$ dB for RSMA increases WSAoI by 38.5%. This increase is comparatively higher when user 1's distance is kept at $d_1 = 3$. Comparing Figure 5.31(a) with Figure 5.31(c), it is concluded that decreasing the far user's distance from $d_2 = 6$ to $d_2 = 4$ is more effective on reducing WSAoI when the near user is at $d_1 = 3$ than at $d_1 = 2$.

Figure 5.31(b) shows that increasing user 2's distance from $d_2 = 4$ to $d_2 = 6$ under $w_2 > w_1$ while keeping user 1's distance constant ($d_1 = 2$) under $\rho = 13$ dB for RSMA increases WSAoI by 69.6%. This increase is comparatively higher when user 1's distance is kept at $d_1 = 3$. Comparing Figure 5.31(b) with Figure 5.31(d), it can be concluded that decreasing the far user's distance from $d_2 = 6$ to $d_2 = 4$ is more effective on reducing WSAoI when the rear user is at $d_1 = 3$ than at $d_1 = 2$.

A comparison of Figure 5.31(a) with 5.31(b), and Figure 5.31(c) with 5.31(d) shows effect of the user weight on WSAoI. It can be concluded from the comparisons that increasing the weight of the user with lower rate decreases WSAoI. This effect seems to be higher when the near user's distance is higher.

It could be inferred from the comparison of Figure 5.29 with Figure 5.31, and Figure 5.28 with Figure 5.30 that a decrease of the user weight with higher rate or a increase of the user weight with lower rate yields to a decrease in WSAoI.

Table 5.23: Simulation parameters for age-energy tradeoff under equal common, unequal private target rates and unequal user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$R_{c,1}^* = R_{c,2}^*$	0.15, 0.18
$R_{p,1}^*, R_{p,2}^*$	(0.85,0.65),(0.65,0.85),(0.82,0.62),(0.62,0.82)
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (2,6), (3,4), (3,6)

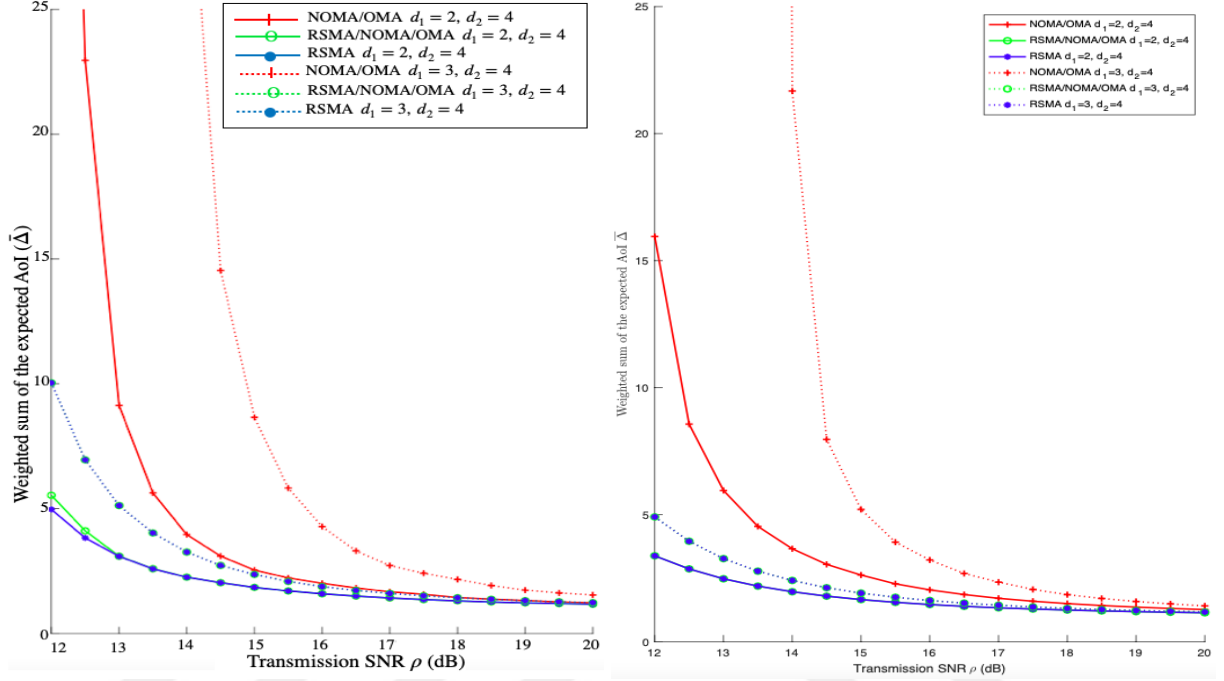
This observation can also be stated in terms of λ_c . To decrease WSAoI, weight of the user with larger λ_c should be increased when $R_1^* > R_2^*$, and weight of the user with smaller λ_c should be increased when $R_2^* > R_1^*$.

5.4.5 Age-Energy Tradeoff Under Equal Common Target Rates, Unequal Private Target Rates and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

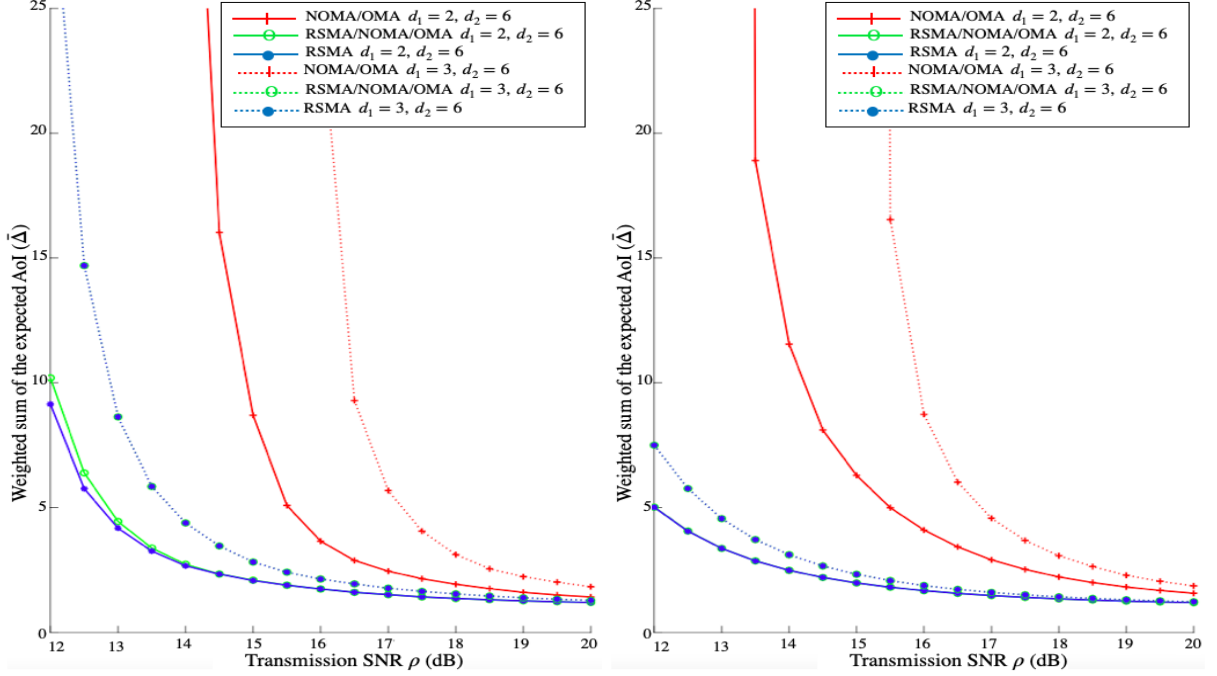
Age-energy tradeoff under unequal target rates and unequal user weights with equal common target rates while changing private target rates is investigated for different values for distances of users, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are shown in the Table 5.23, and in Figure 5.32 for $R_1^* > R_2^*$, $\{[w_1 > w_2], [w_2 > w_1]\}$ and in Figure 5.33 for $R_1^* < R_2^*$, $R_{c,1}^* = R_{c,2}^* = 0.18$, $\{[w_1 > w_2], [w_2 > w_1]\}$. The simulation results for $R_{c,1}^* = R_{c,2}^* = 0.15$ are given in Appendix D.1.

Figure 5.32 and Figure 5.33 show that RSMA scheme outperforms NOMA/OMA schemes for both $R_1^* > R_2^*$ ($R_{p,1}^* > R_{p,2}^*$) and $R_2^* > R_1^*$ ($R_{p,1}^* > R_{p,2}^*$),



(a) $d_2 = 4, d_1 = 2, 3 [(w_1 = 0.7) > (w_2 = 0.3)]$

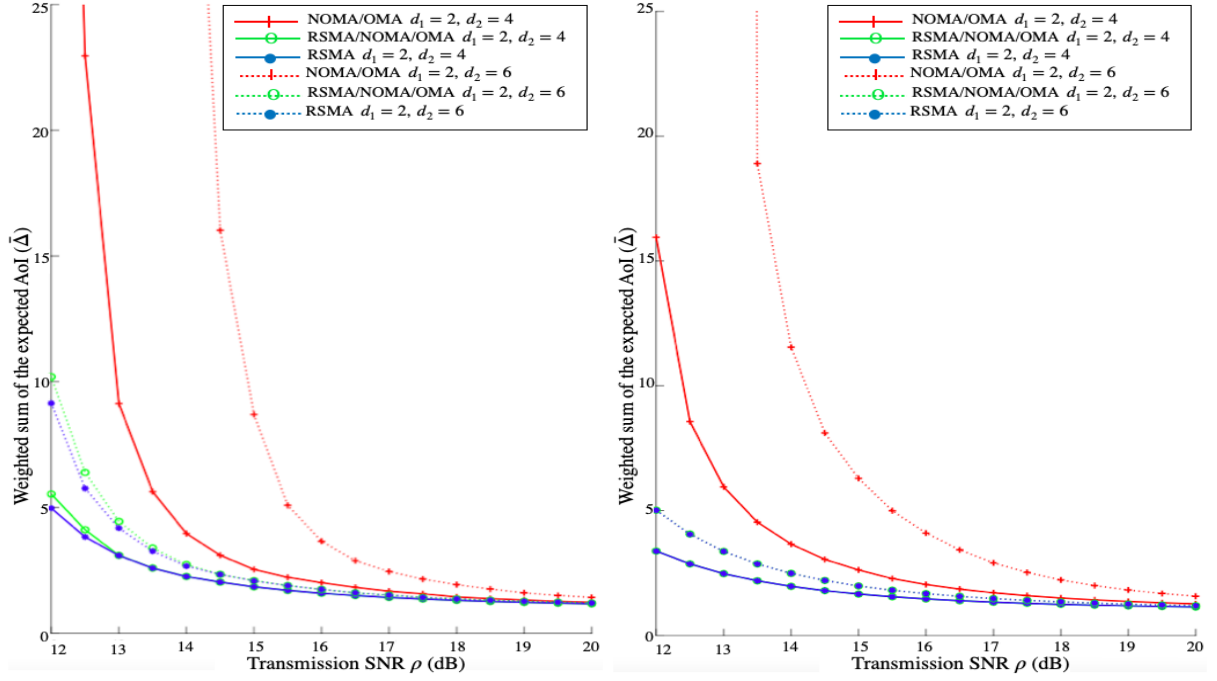
(b) $d_2 = 4, d_1 = 2, 3 [(w_2 = 0.7) > (w_1 = 0.3)]$



(c) $d_2 = 6, d_1 = 2, 3 [(w_1 = 0.7) > (w_2 = 0.3)]$

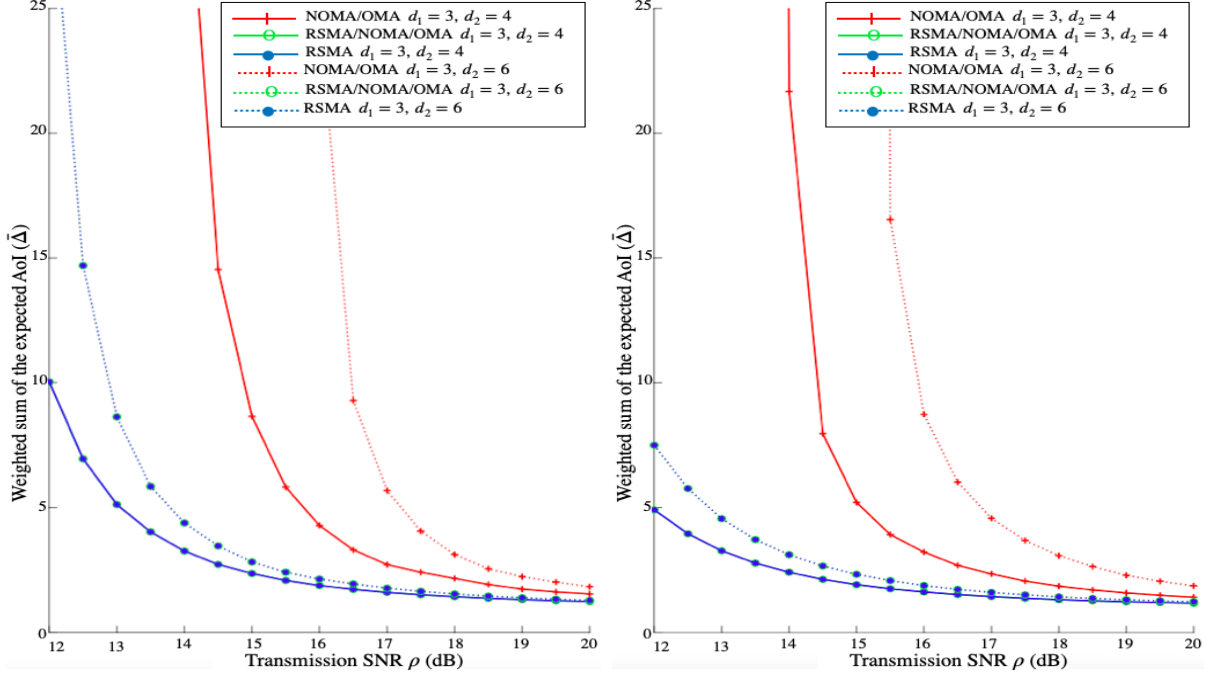
(d) $d_2 = 6, d_1 = 2, 3 [(w_2 = 0.7) > (w_1 = 0.3)]$

Figure 5.28: Age-energy tradeoff for user distances $d_2 = \text{constant}$, d_1 is changed [$R_1^* = 1.0, R_2^* = 0.8$]



(a) $d_1 = 2, d_2 = 4, 6 [(w_1 = 0.7) > (w_2 = 0.3)]$

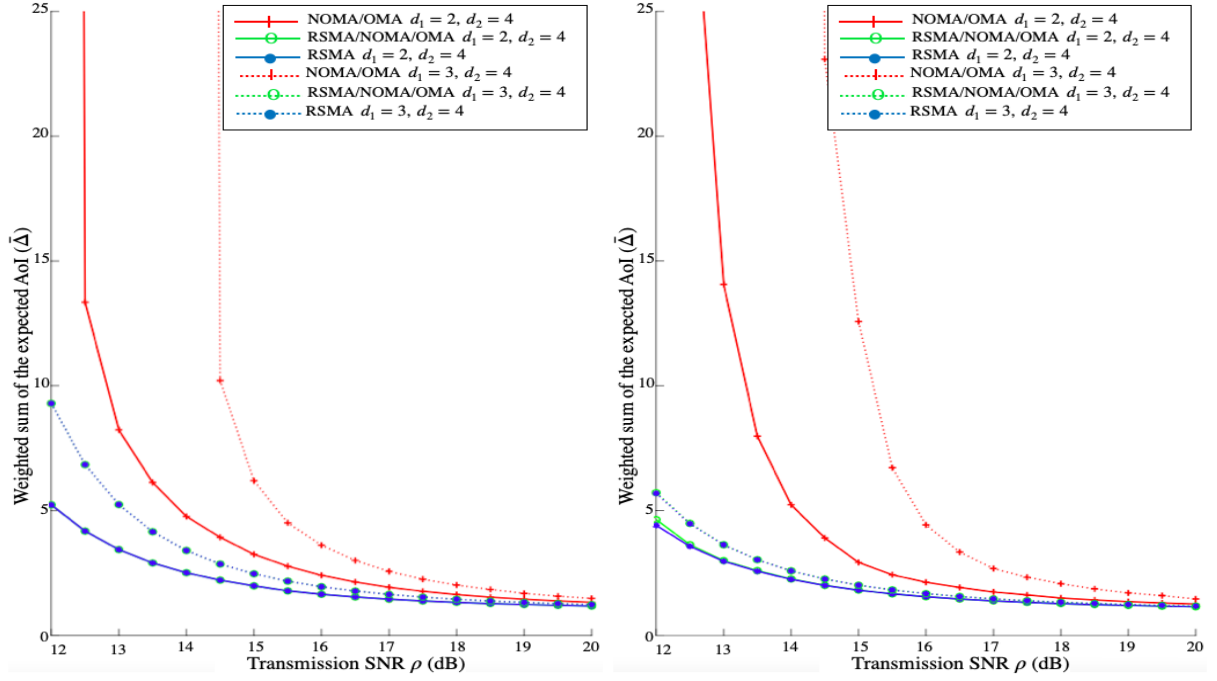
(b) $d_1 = 2, d_2 = 4, 6 [(w_2 = 0.7) > (w_1 = 0.3)]$



(c) $d_1 = 3, d_2 = 4, 6 [(w_1 = 0.7) > (w_2 = 0.3)]$

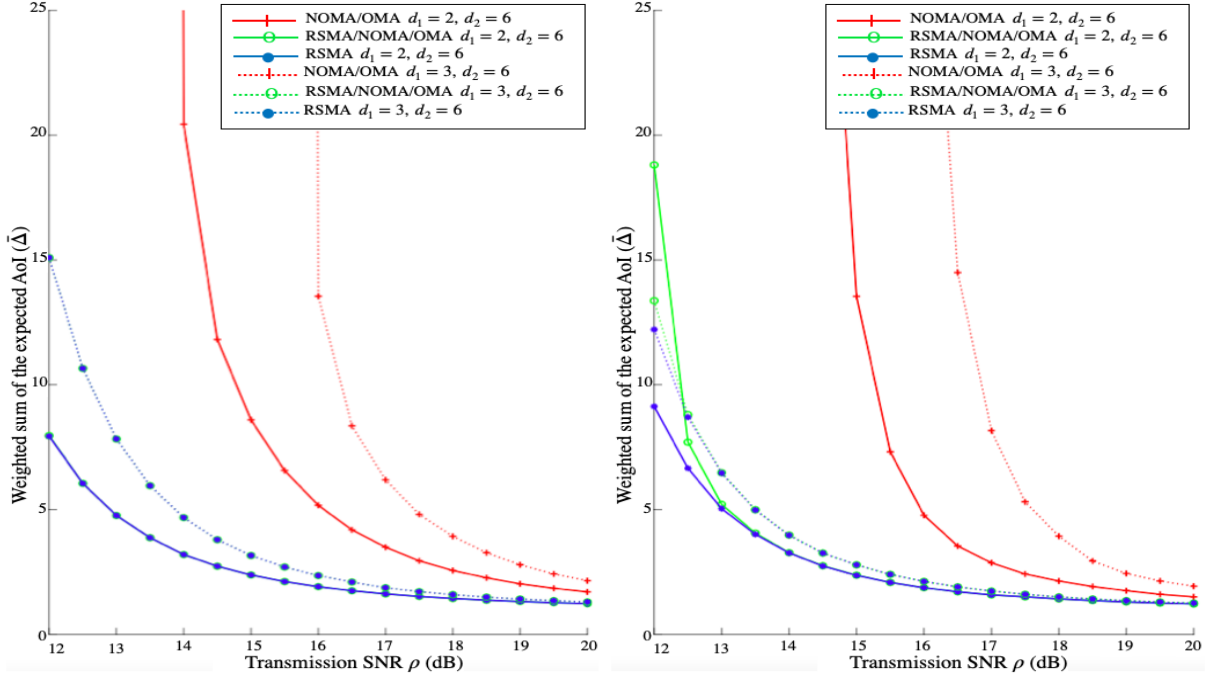
(d) $d_1 = 3, d_2 = 4, 6 [(w_2 = 0.7) > (w_1 = 0.3)]$

Figure 5.29: Age-energy tradeoff for user distances $d_1 = \text{constant}$, d_2 is changed [$R_1^* = 1.0, R_2^* = 0.8$]



(a) $d_2 = 4, d_1 = 2, 3 [(w_2 = 0.7) > (w_1 = 0.3)]$

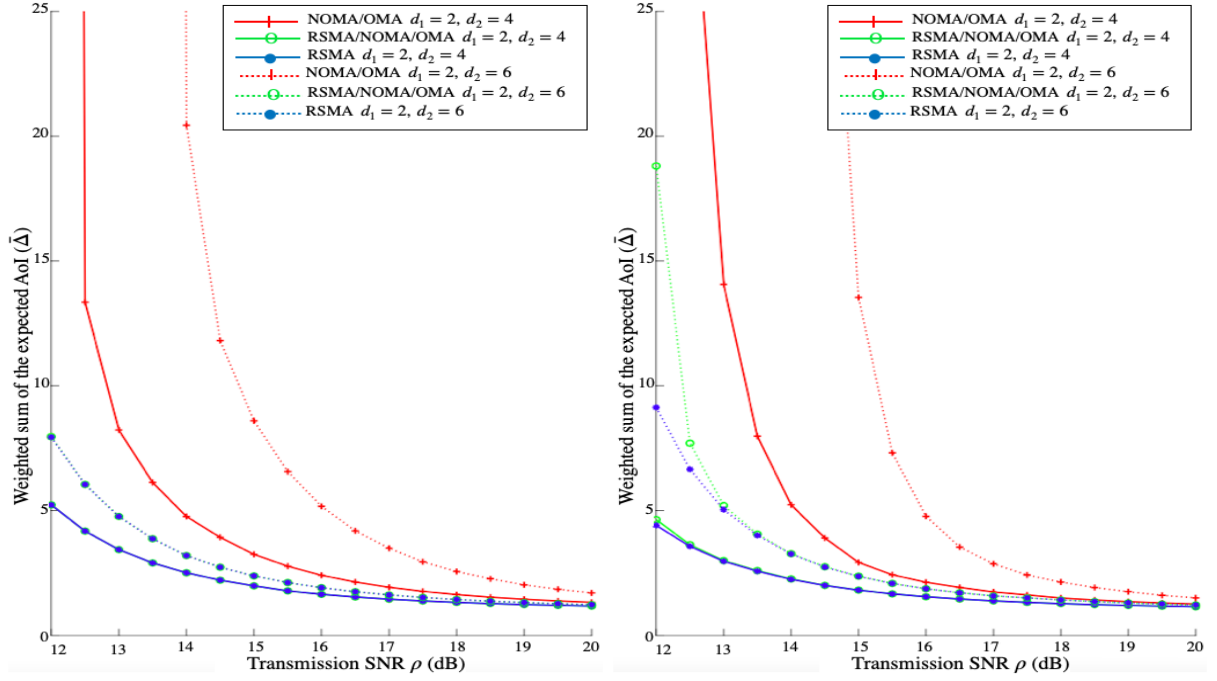
(b) $d_2 = 4, d_1 = 2, 3 [(w_1 = 0.7) > (w_2 = 0.3)]$



(c) $d_2 = 6, d_1 = 2, 3 [(w_2 = 0.7) > (w_1 = 0.3)]$

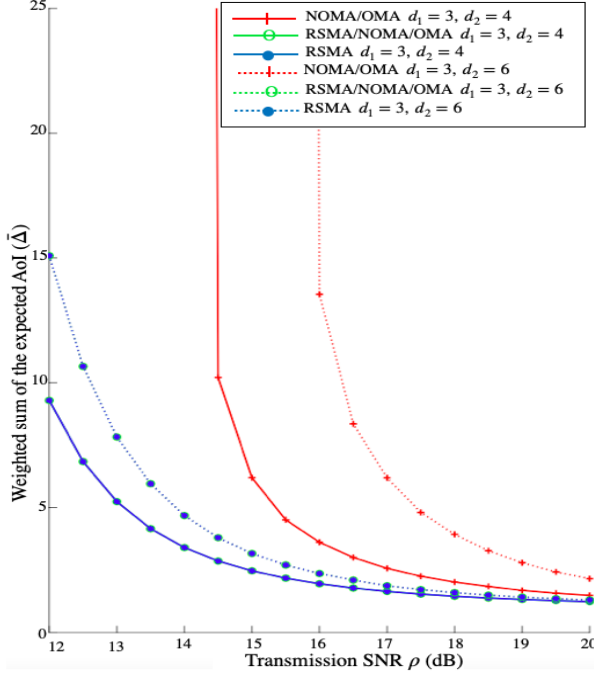
(d) $d_2 = 6, d_1 = 2, 3 [(w_1 = 0.7) > (w_2 = 0.3)]$

Figure 5.30: Age-energy tradeoff for user distances $d_2 = \text{constant}$, d_1 is changed
 $[R_1^* = 0.8, R_2^* = 1.0]$

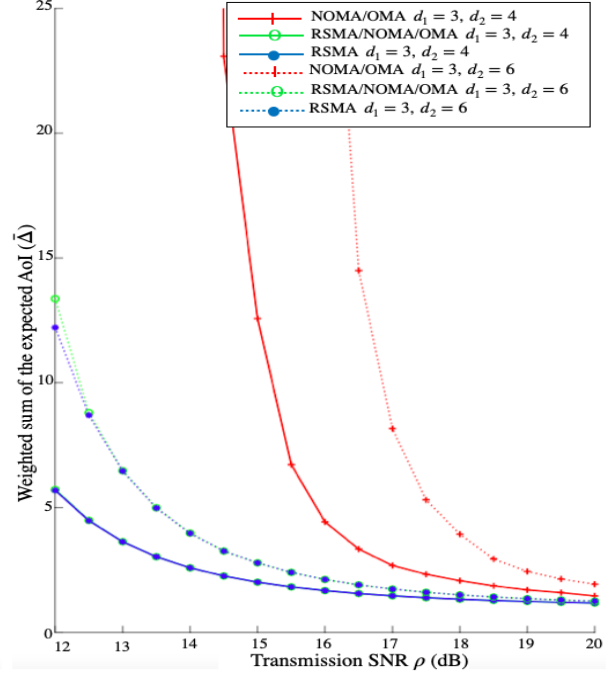


(a) $d_1 = 2, d_2 = 4, 6 [(w_2 = 0.7) > (w_1 = 0.3)]$

(b) $d_1 = 2, d_2 = 4, 6 [(w_1 = 0.7) > (w_2 = 0.3)]$

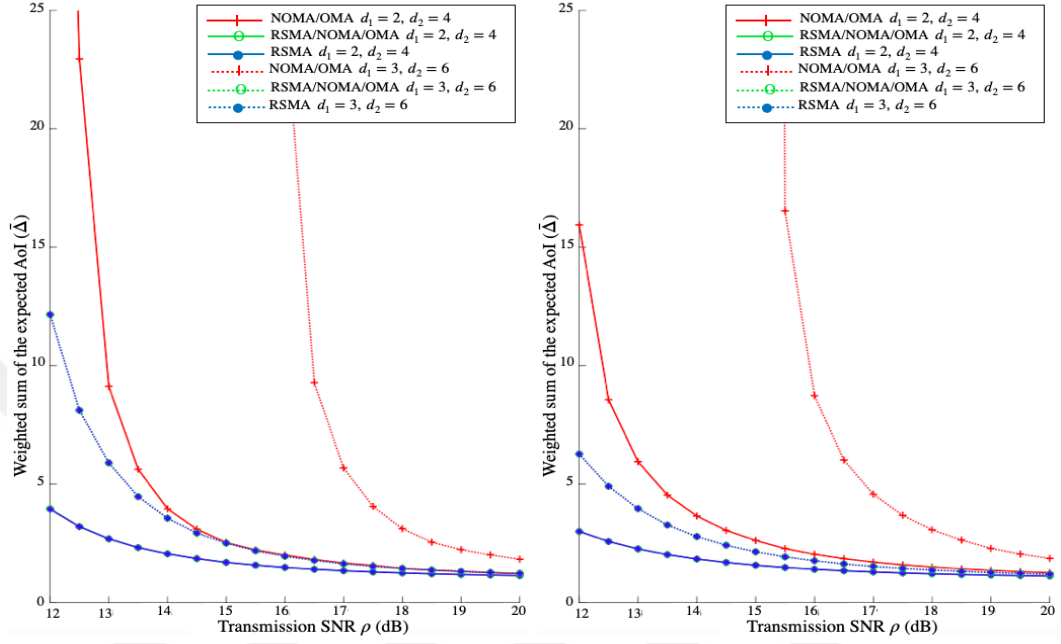


(c) $d_1 = 3, d_2 = 4, 6 [(w_2 = 0.7) > (w_1 = 0.3)]$



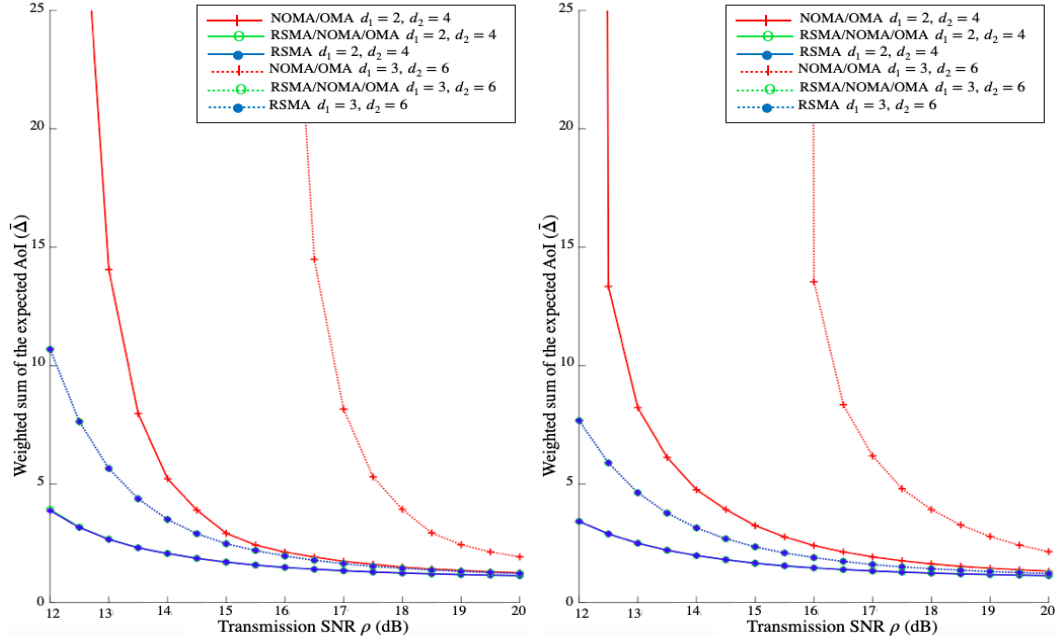
(d) $d_1 = 3, d_2 = 4, 6 [(w_1 = 0.7) > (w_2 = 0.3)]$

Figure 5.31: Age-energy tradeoff for user distances $d_1 = \text{constant}$, d_2 is changed $[R_1^* = 0.8, R_2^* = 1.0]$



(a) $d_2/d_1 = 2$ $[(w_1 = 0.7) > (w_2 = 0.3)]$ (b) $d_2/d_1 = 2$ $[(w_2 = 0.7) > (w_1 = 0.3)]$

Figure 5.32: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = 1.0) > (R_2^* = 0.8), (R_{c,1}^* = R_{c,2}^* = 0.18)]$



(a) $d_2/d_1 = 2$ $[(w_1 = 0.7) > (w_2 = 0.3)]$ (b) $d_2/d_1 = 2$ $[(w_2 = 0.7) > (w_1 = 0.3)]$

Figure 5.33: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_2^* = 1.0) > (R_1^* = 0.8), (R_{c,1}^* = R_{c,2}^* = 0.18)]$

for both user distances, and at all ranges of SNR (ρ) (0.12 - 0.20). This observation becomes much obvious at low SNR values, and the user distance from the BS is increased. It is also observed that both RSMA and RSMA/NOMA/OMA schemes take the same actions, and the related curves coincide.

Comparing Figure 5.32 with Figure 5.38 show that, without changing user weights and target rates, while keeping the user 2's common target rate constant, increasing user 1's common target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher.

Similarly, comparing Figure 5.33 with Figure 5.39 show that, without changing the user weights and target rates, while keeping the user 1's common target rate constant, increasing user 2's common target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher. Considering this observation and the observation given in the previous paragraph, it can be concluded that, without changing the user weights and target rates, while keeping one user's common target rate constant, increasing the other user's common target rate decreases WSAoI substantially.

Age-energy tradeoff study for change of private target rate of one user while keeping common target rates of both users and private target rate of other user constant might also be shown through comparing Figure 5.18(b) with Figure 5.32(a) and Figure 5.33(a) for $w_1 > w_2$, and Figure 5.19(b) with Figure 5.32(b) and Figure 5.33(b) for $w_1 < w_2$. For convenience of showing different figures together, these comparisons are re-given in Figure 5.34, Figure 5.35, Figure 5.36 and Figure 5.37.

Comparisons of Figure 5.34, Figure 5.35, Figure 5.36, and Figure 5.37 show that, decreasing one user's private target rate, while keeping both users' common target rates, user weights and the other user's private rate constant, decreases WSAoI substantially for both $w_1 > w_2$ and $w_1 < w_2$ cases. Reduction in WSAoI is the highest if the far user's private rate is decreased when far user's weight is

higher, and the smallest if its weight is less than the rear user's weight. Reduction due to decrease of rear user's private rate, when its weight is less, is larger than the case when its weight is less than the far user's weight.

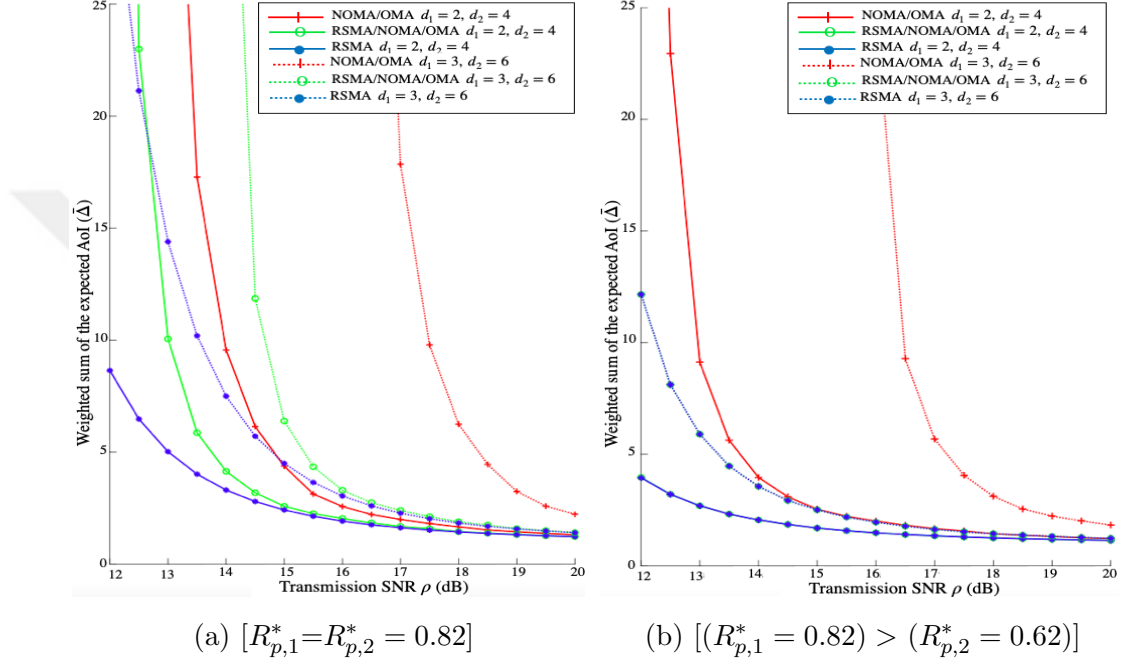


Figure 5.34: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.7, w_2 = 0.3)]$, equal common target rates and changing private target rates]

5.4.6 Age-Energy Tradeoff Under Equal Private Target Rates, Unequal Common Target Rates and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under unequal target rates and unequal user weights with equal private target rates while changing common target rates is investigated for different values for distances of users from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on

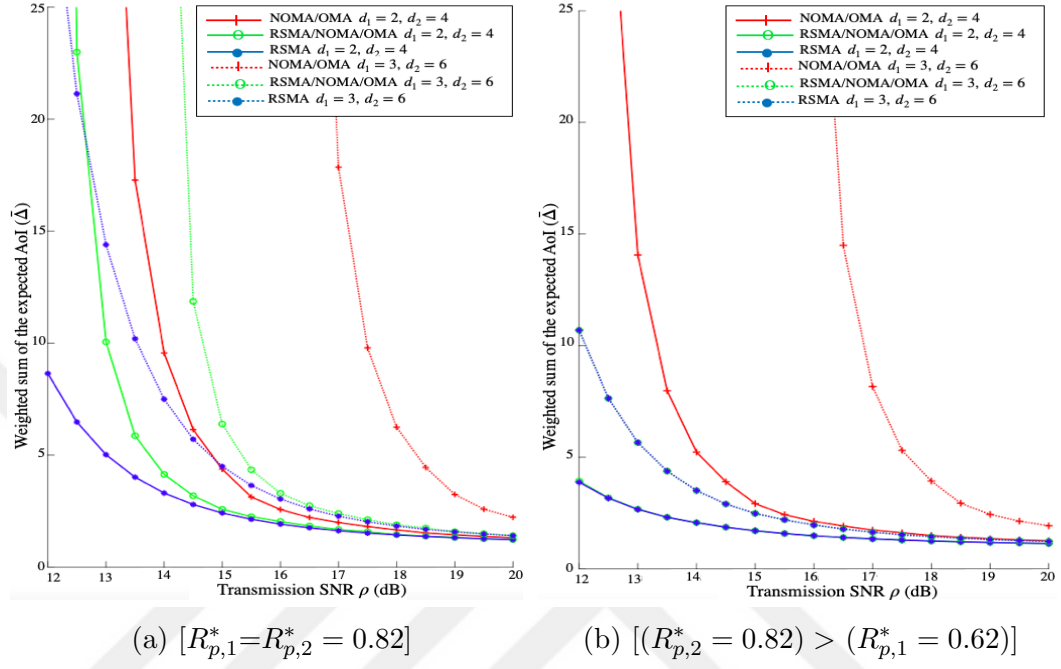


Figure 5.35: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.7, w_2 = 0.3)]$, equal common target rates and changing rear user's private target rate]

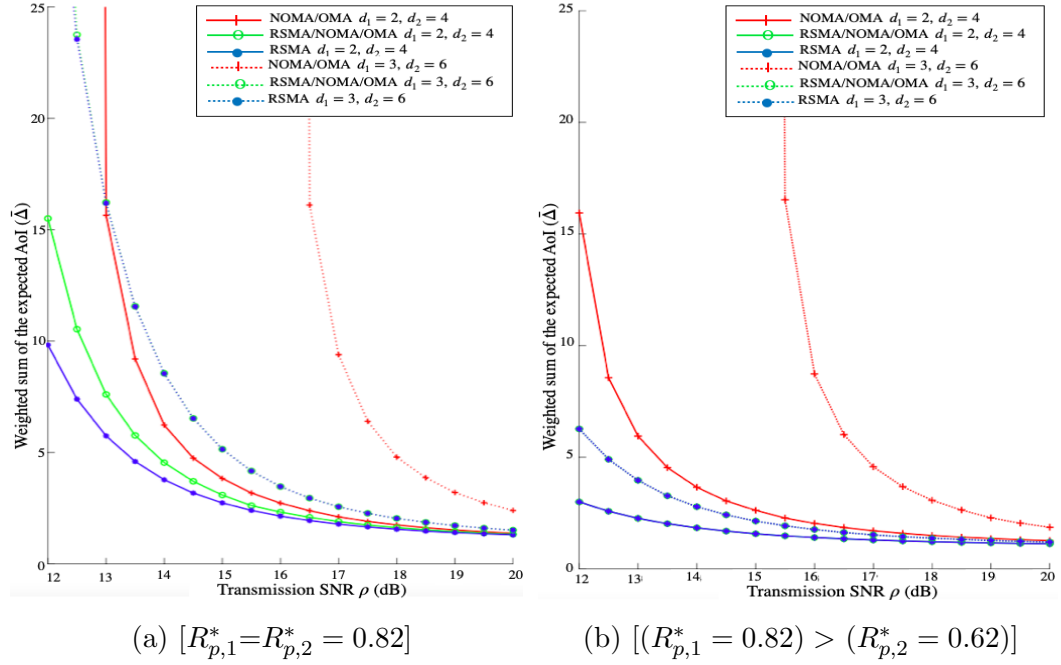


Figure 5.36: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.3, w_2 = 0.7)]$, equal common target rates and changing far user's private target rate]

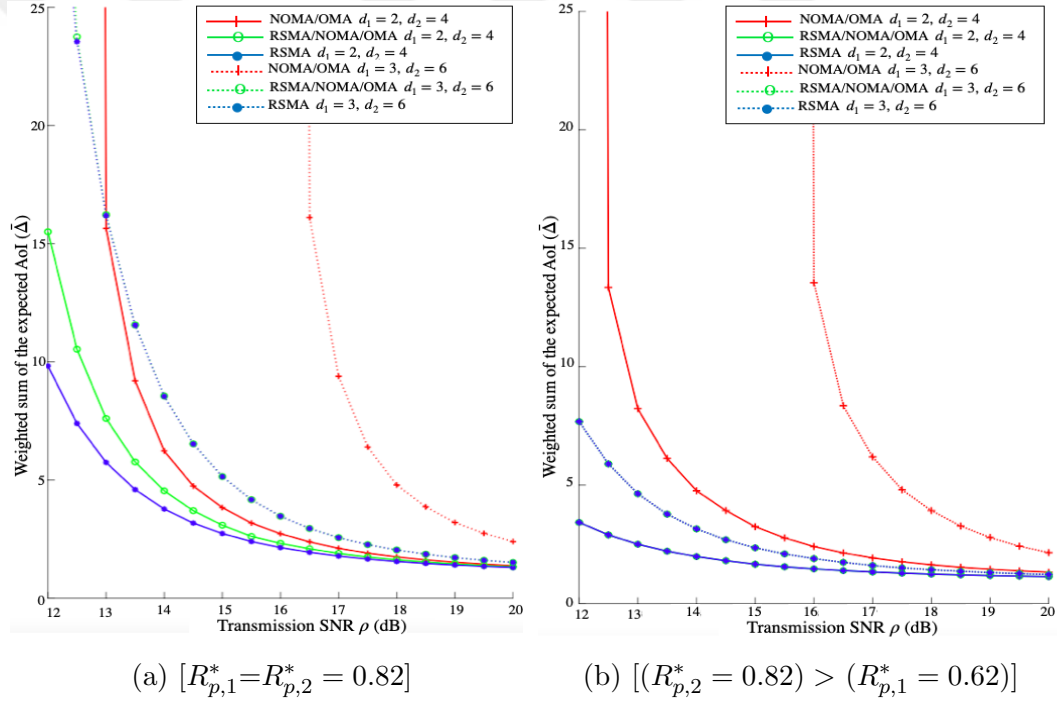


Figure 5.37: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.7, w_2 = 0.3), \text{equal common target rates and changing rear user's private target rate}]$

Table 5.24: Simulation parameters for age-energy tradeoff under equal private, unequal common target rates and unequal user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$R_{p,1}^* = R_{p,2}^*$	0.62, 0.65
$R_{c,1}^*, R_{c,2}^*$	(0.38,0.18),(0.18,0.38),(0.35,0.15),(0.15,0.35)
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (2,6), (3,4), (3,6)

WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are shown in the Table 5.24, and in Figure 5.38 for $R_1^* > R_2^*$, $\{[w_1 > w_2], [w_1 < w_2]\}$ and in Figure 5.39 for $R_1^* < R_2^*$, $R_{p,1}^* = R_{p,2}^* = 0.62$, $\{[w_1 > w_2], [w_1 < w_2]\}$. The simulation results for $R_{p,1}^* = R_{p,2}^* = 0.65$ are given in Appendix D.2.

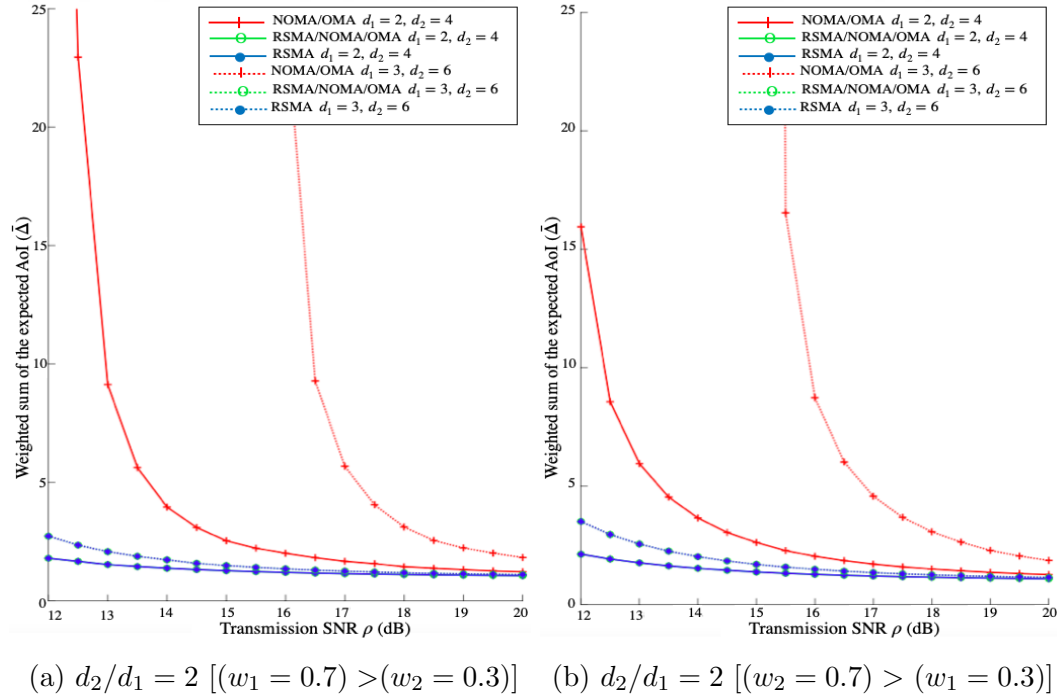


Figure 5.38: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = 1.0, R_2^* = 0.8), (R_{p,1}^* = R_{p,2}^* = 0.62)]$

Figure 5.38 and Figure 5.39 show that RSMA scheme outperforms NOMA/OMA schemes for both $R_1^* > R_2^*$ ($R_{c,1}^* > R_{c,2}^*$) and $R_2^* > R_1^*$ ($R_{c,1}^* > R_{c,2}^*$),

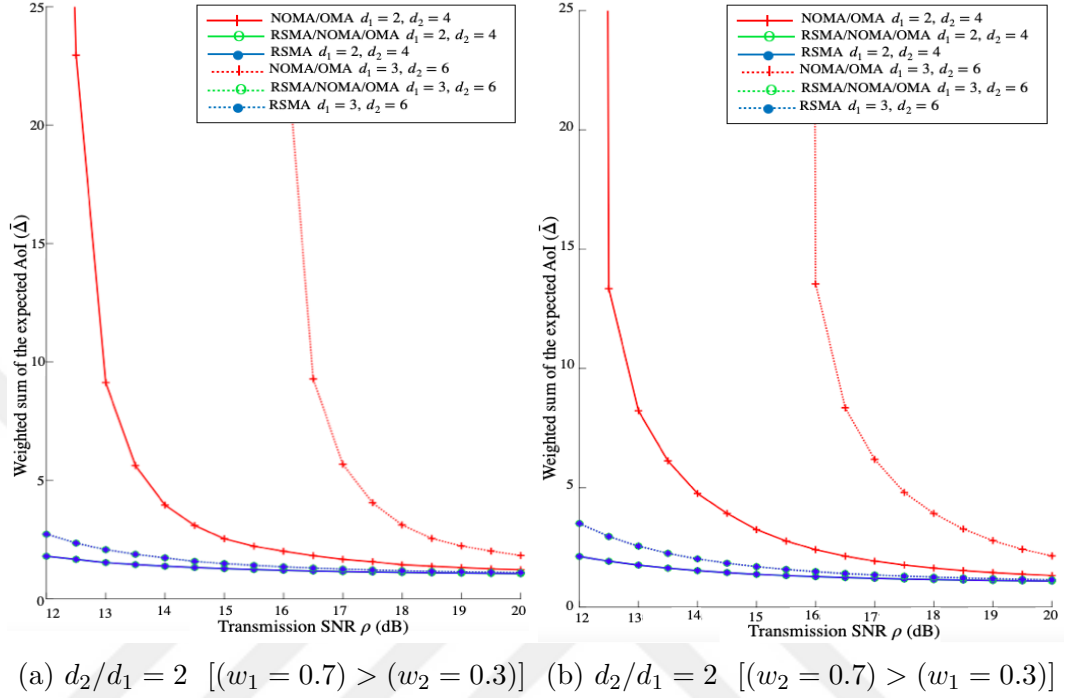


Figure 5.39: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = 0.8, R_2^* = 1.0)$, equal private target rates]

for both user distances, and at all ranges of SNR (ρ) (0.12 - 0.20). This observation becomes much obvious at low SNR values, and the user distance from the BS is increased. It is also observed that both RSMA and RSMA/NOMA/OMA schemes take the same actions, and the related curves coincide.

Comparing Figure 5.32 with Figure 5.38 show that, without changing user weights and target rates, while keeping the user 2's private target rate constant, decreasing user 1's private target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher.

Similarly, comparing Figure 5.33 with Figure 5.39 show that, without changing the user weights and target rates, increasing user 2's private target rate while keeping the user 1's private rate constant decreases WSAoI. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher. Considering this observation and the observation given in the previous paragraph, it can be concluded that, without

changing the user weights and target rates, decreasing one user's private target rate while keeping the other user's private target rate constant decreases WSAoI substantially.



Chapter 6

Conclusions and Future Work

6.1 Conclusions

In this thesis, an adaptive scheme including RSMA, NOMA and OMA is studied. We focus on the massive MTC use-case of the future generation networks and incorporate RSMA, a multiple access method proposed as a strategy for the other two predicted use cases, namely URLLC and eMBB.

Motivated by the existing results of RSMA overperforming SDMA and NOMA in energy efficiency, we propose an adaptive policy with RSMA that minimizes WSAoI of the network.

Under the green banner of the adaptive scheme, we investigate also the tradeoff between energy and WSAoI of the network. The problems are setup as MDP problems. Besides a switching type optimal, also a lower complexity suboptimal policy that maximizes AoI drop in each time slot, is proposed. Effect of main parameters (target rate, user weight, distance of user to BS, transmission SNR) on the performance metrics (WSAoI, and age-energy tradeoff) are analyzed by varying values of one parameter while keeping the others constant. The analyses are made under various combinations of simulation conditions; {user 1's target

rate is larger than user 2's target rate}, {user 2's target rate is larger than user 1's target rate}, {user 1's weight is larger than user 2's weight}, and {user 2's weight is larger than user 1's weight}.

Sub-optimal policy provides exactly the same results with optimal policy at small user distances to BS, and at high SNR values. However, a small gap is observed between the results of the two policies at very low SNR values when the user distance is comparatively small, e.g. when $d_1 = 2, d_2 = 4$. The gap increases at high user distances, e.g. $d_1 = 3, d_2 = 6$. Computation time with sub-optimal policy, due to its low computation complexity in comparison to computation complexity of optimal policy, is substantially lower than with optimal policy.

When age difference of two users is high, BS tends to increase power of the user with higher age. The increase rate depends also on outage probability of user. When age difference exceeds a certain level, then BS serves the user with high age through selection of OMA. However, if age difference is small, both users are served through RSMA or NOMA. When the common part of user message is high, RSMA is selected. Otherwise, NOMA is the scheme to be used. Since OMA and NOMA are special forms of the generalized RSMA, RSMA scheme outperforms NOMA/OMA scheme in most of the scenarios.

It is shown that when the target rates for common messages are greater than a certain value, RSMA is preferred over NOMA and OMA. This certain value decreases with increasing user distances to BS. RSMA scheme selection percentage increases with increasing user common rate. RSMA domination becomes much obvious when the user distances are increased. With increasing user distances to BS, RSMA and OMA scheme selection increases and NOMA scheme selection decreases. Below the certain value, increasing the user common rate increases NOMA scheme selection rate with respect to OMA scheme. Under the same conditions, RSMA and NOMA scheme selection percentages increase with increasing transmission SNR.

More power is allocated to user with greater user weight. If further user has greater weight, the policy tries to increase the the common power allocation factor

indicating ratio of common message's power to total transmit power (α_c) in an action.

WSAoI decreases as the transmission SNR increases and distances to BS decreases for all schemes. For the same user weight, user distance to BS, SNR, and common target rate conditions, WSAoI is higher for $R_2^* > R_1^*$ than for $R_1^* > R_2^*$.

It can be concluded that, without changing the user weights and target rates, increasing one user's common target rate while keeping the other user's common target rate constant, decreases WSAoI substantially. Reducing near user's common rate while keeping far user's common rate constant is more effective on reducing WSAoI than reducing far user's common rate while keeping near user's common rate constant. Similarly, without changing the user weights and target rates, decreasing one user's private target rate while keeping the other user's private target rate constant, decreases WSAoI substantially. Similarly, decreasing one user's private target rate, while keeping both users' common target rates, user weights and the other user's private rate constant, decreases WSAoI substantially for both $w_1 > w_2$ and $w_1 < w_2$ cases. Reduction in WSAoI becomes highest if the far user's private rate is decreased when far user's weight is higher, and smallest if far user's weight is less than the rear user's weight.

It is also highlighted that RSMA scheme outperforms OMA and NOMA schemes in terms of tradeoff between WSAoI of the network and power consumption. When RSMA scheme is selected, at SNR values of 14 dB, 15 dB, and 16 dB, WSAoI is in average, respectively 35.8%, 15.7%, and 12.7% less than NOMA/OMA schemes. By using RSMA scheme instead of NOMA/OMA scheme, power consumption can be reduced in average 65.8%, 62.3%, and 59.6% for the selected WSAoI values of 4, 3, and 2, respectively.

It can also be concluded that, for a selected user distance case for the users, decreasing user weight of user with higher target rate conditions or increasing user weight of user with lower target rate conditions decreases WSAoI. This conclusion is not observed when $R_2^* > R_1^*$ and far user's distance is very large.

6.2 Future Work

Some of problems for future work include interference and relay channels with imperfect CSIT, role of RSMA in achieving limits of broadcasting, RSMA's constraints, RSMA's SE and EE performance analysis, optimization of max-min fairness of RSMA for multi-user network MIMO and a comparative study on RSMA with linear and nonlinear precoding.

A new approach to cross-layer design of RSMA, design of RSMA for millimeter-wave network MIMO, security provisioning aspects in RSMA, RSMA design aspects for various type of networks, RSMA design for multi-cell MIMO and standardization issues of RSMA are some of the potential subjects that need further attention. The scheme including RSMA could be extended to short packet communications. The average block error rate expressions could be derived and the transition probabilities could be expressed in terms of the derived expressions. Different channel models might be used to further investigate the tradeoff between AoI and energy.

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Appendix A

Proof of Theorem 1

The studies in this thesis are based on an average optimal stationary policy treated by MDP. Basic definitions and concepts are given below before starting with proof of Theorem 1. They are rephrased from [80].

A.1 Introduction

When a system is in state s , an action from an action set, shown as $A(s)$, is chosen.

With given s and chosen action a , a reward to be maximized (or cost to be minimized) is obtained. Reward at t for a in s is shown as $r_s^t(a)$; if it does not depend on t , $r_s(a)$ is used in place of $r_s^t(a)$.

Next step is decided by transition rule. Probability for having state π in the next step is $p_s^t(a)$. When transition is independent of time, problem is stationary when there is a function f on S satisfying $f(s) \in A(s)$ and transition probability is indicated as $p_{sf}(a)$ [80]. Process has a planning horizon that might be finite or infinite.

MDP's objective is to define a policy that optimizes system performance which is measured by a utility function f [80].

A.2 Optimal Control Problem

A control model, $\{S, (A(s) \subset A, s \in S), P(\cdot|s, a), r(s, a)\}$ is defined. S, A are assumed as Borel spaces. P is transition rule.

Stationary policy is indicated as π . A set of π is Π .

$$P_s^\pi(s_t + 1 \in D|h_t, a_t) = P(D|s_t, a_t) \quad (\text{A.1})$$

where $h_t = (a_0, a_1, \dots, s_{t-1}, s_t) \in H_t$, $D \in B(S)$. Expectation operator corresponding to P_s^π is E_s^π . When $\pi := f \in F$, $\{s_t\}$ is $P(\cdot|s, f(s))$.

Average reward $\bar{V}(\cdot, \cdot)$ and related function $\bar{V}^*(\cdot)$ with $s \in S$, $\pi \in \Pi$;

$$\bar{V}(s, \pi) := \lim_{n \rightarrow \infty} \sup \frac{E_s^\pi[\sum_{t=0}^{n-1} r(s_t, a_t)]}{n} \quad (\text{A.2})$$

$$\bar{V}^*(s) := \inf_{\pi \in \Pi} \bar{V}(s, \pi) \quad (\text{A.3})$$

$\pi^* \in \Pi$ is average optimal when $\bar{V}(s, \pi^*) = \bar{V}^*(s)$, $s \in S$.

For initial state s_0 , choosing action a_t with probability $\pi_t(a_t|s_t)$, policy π 's horizon average reward is expressed as (4.1). In (4.1), $C(\pi, s_0)$ is used instead of V :

$$C(\pi, s_0) = \lim_{T \rightarrow \infty} \sup \frac{1}{T} [\sum_{k=0}^{T-1} E_{s_0}^\pi[r(s_k, \alpha_k)|s_0]] \quad (\text{A.4})$$

The decision policy in the thesis is based on minimisation of $C(\pi, s_0)$. This problem is transferred into MDP. Theorem 1 given in Chapter 4 is repeated below for convenience of the reader.

Theorem 1. There exists a constant I^* , a bounded function $f(\Delta_1, \Delta_2): S \rightarrow \mathbb{R}$, a stationary and deterministic policy π^* , satisfying equation of average cost optimality,

$$I^* + f(\Delta_1, \Delta_2) = \min_{a_t \in A} (w_1 \Delta_{1,t} + w_2 \Delta_{2,t} + \mathbb{E}[f(\hat{\Delta}_1, \hat{\Delta}_2)]) \quad (\text{A.5})$$

where π^* is optimal policy, I^* is (Δ_1, Δ_2) taking action a_t .

A.3 Existence of Average Optimal Stationary Policy

Conditions of average optimal stationary policy existence are proved by Guo and Zhu [81]. The referenced study is adapted to Theorem 1 which is stated in the main body of the thesis, and restated here as adapted for the completeness of the thesis. For proof, we should verify optimality conditions that are given in the Reference [81], which are restated below.

A.3.1 Optimality Conditions

Since $r(s, a)$, might be unbounded, *expected growth* condition (A.1), is used to warrant finiteness of $V(s, \pi)$.

Assumption A.1.

(i) Positive constants, $m, \beta < 1$, function $w \geq 1$, on S exist;

$$\int_S w(y) P(dy|s, a) \leq \beta w(s) + m \text{ for all } (s, a) \in K \quad (\text{A.6})$$

(ii) A constant, $M > 0$, exists satisfying $|r(s, a)| \leq Mw(s, a) \in K$.

Remark A.1. Assumption A.1 (i) is a statement of "Lyapunov like inequality". m in A.1 could be changed with a non-negative measurable *bounded* function, $m(s)$, on S .

Lemma A.1. Assume that Assumption A.1 is correct;

(a) $E_s^\pi[w(s_t)] \leq \beta^t w(s) + [(1 - \beta^t)/(1 - \beta)]m$ when $t \geq 0, s \in S, \pi \in \Pi$

(b) $|\bar{V}(s, \pi)| \leq mM/(1 - \beta)$ when $t \in S$, $\pi \in \Pi$.

Proof (a) Lemma A.1(a) can be proven by using induction. When $t \geq 1$, by using Assumption A.1(i) and A.1 we have

$$E_s^\pi[w(s_t)|s_0, a_0, \dots, s_{t-1}, a_{t-1}] = \int_S w(y)P(dy|s_{t-1}, a_{t-1}) \leq \beta w(s_{t-1}) + m \quad (\text{A.7})$$

and, so,

$$\begin{aligned} E_s^\pi[w(s_t)] &\leq \beta E_s^\pi[w(s_{t-1})] + m \\ &\leq \beta^2 E_s^\pi[w(s_{t-2})] + m + m\beta \leq \dots \leq \beta^t w(s) + m + m\beta + \dots + m\beta^{t-1} \\ &= \beta^t w(s) + \frac{1 - \beta^t}{1 - \beta} m \end{aligned} \quad (\text{A.8})$$

Lemma A.1(a) is verified. (b) is verified from Assumption A.1(ii) and (a) since $0 < \beta < 1$.

In the thesis, there are positive constants namely M , m and $\beta < 1$, $w(s) \geq 1$, where $s = (\Delta_1, \Delta_2) \in S$ with a function of reward/cost that is valid for s-a pairs; $r(s, a) = w_1\Delta_1 + w_2\Delta_2 = w(s, a)$, $|r(s, a)| \leq Mw(s)$ and

$$\Sigma_{\hat{s} \in S} w(\hat{s}|s, a) \leq \beta w(s) + m \quad (\text{A.9})$$

$v_1, v_2 \in B_w(S)$, with $s_0 \in S$, satisfying;

$$v_1(s) \leq h_\alpha(s) \leq v_2(s) \quad (\text{A.10})$$

where $B_w(S) := \{u : \|u\|_w < \infty\}$ indicates Banach space, $\|u\|_w := \sup_{s \in S} w(s)^{-1}|u(s)|$ indicates weighted supremum, $h_\alpha(s) = V_\alpha(s) - V_\alpha(s_0)$ for all $s \in S$.

In the thesis, for saying that Assumption A.1 is valid, it is shown that if $w(s) = w_1\Delta_1 + w_2\Delta_2$, $m > 1$, then there is β satisfying, $\max_a \leq \beta < 1$, where $\max_a$ is:

$$\begin{aligned}
& \max_a \left\{ \frac{w_1 \Delta_1 P_1^{OMA}(a_t = 0, \alpha_c = 0) + w_2 \Delta_2 + 1 - m}{w(s)}, \right. \\
& \quad \frac{w_1 \Delta_1 + w_2 P_2^{OMA}(a_t = N, \alpha_c = 0) \Delta_2 + 1 - m}{w(s)}, \\
& \quad \frac{w_1 P_1^{NOMA}(a_t, \alpha_c = 0) \Delta_1 + w_2 P_2^{NOMA}(a_t, \alpha_c = 0) \Delta_2 + 1 - m}{w(s)}, \\
& \quad \left. \frac{w_1 P_1^{RSM A}(a_t, \alpha_c, \lambda_{c,1}) \Delta_1 + w_2 P_2^{RSM A}(a_t, \alpha_c, \lambda_{c,2}) \Delta_2 + 1 - m}{w(s)} \right\} \tag{A.11}
\end{aligned}$$

Assumption A.2.

For each fixed $s \in S$;

- (i) $A(s)$ is compact.
- (ii) $c(s, a)$ is lower semi-continuous with $a \in A(s)$, $\int_S u(y) P(dy|s, a)$ continuous with $a \in A(s)$ for u on S , $u := w$ as in Assumption A.1.

Remark A.2. Assumption A.2 is varified if $A(s)$ is finite for $s \in S$.

Lemma A.2. Under Assumptions A.1 and A.2, for $\alpha \in (0, 1)$ following statements are correct.

- (a) $|V_\alpha(s, \pi)| \leq Mw(s)/(1 - \alpha) + mM/[(1 - \beta)(1 - \alpha)]$ for $s \in S$, $\pi \in \Pi$.
- (b) $V_\alpha^*(s)$, meets cost/reward optimality:

$$V_\alpha^*(s) = \min_{a \in A(s)} c(s, a + \alpha \int_S V_{alpha}^*(y) P(dy|s, a) \text{ for } s \in S \tag{A.12}$$

- (c) For $0 < \alpha < 1$, a stationary policy $f_\alpha^*(s)$ exists, satisfying:

$$V_\alpha^*(s, f_\alpha^*) = V_\alpha^*(s) \text{ for all } s \in S \tag{A.13}$$

Proof. By Lemma A.1 and Assumption A.1(ii), we have

$$\begin{aligned}
|V_\alpha(s, \pi)| & \leq M \sum_{t=0}^{\infty} \alpha^t E_s^\pi [w(s_t)] \\
& \leq M \sum_{t=0}^{\infty} \alpha^t [\beta^t w(s) + \frac{1 - \beta^t}{1 - \beta} m] \\
& \leq M \sum_{t=0}^{\infty} \alpha^t [w(s) + \frac{m}{1 - \beta}] \\
& = \frac{Mw(s)}{1 - \alpha} + \frac{Mm}{(1 - \beta)(1 - \alpha)}
\end{aligned} \tag{A.14}$$

Lemma A.2.(a) is verified, (b), (c) are proved in [81].

In the thesis, Assumption A.2 holds since action space of each state is finite.

A new condition (A.3) is defined for proving average optimal stationary policy existence.

Assumption A.3 There are two value functions, v_1 and $v_2 \in S$, with states, $s_0 \in S$ satisfying

$$v_1(s) \leq h_\alpha(s) \leq v_2(s) \text{ for } s \in S, \alpha \in (0, 1) \quad (\text{A.15})$$

with $h_\alpha(s) := V_\alpha^*(s_0)V_\alpha^*(s)$.

Remark A.3. (a) Assumption A.3 is added because $v_1(s)$ may not be below bounded. (b) This assumption is verified if Assumptions A.1 and A.2 and the following condition are met. For $f \in F$ there is a probability measure, μ_f , satisfying

$$\sup_{|u| \leq w} |E_s^f[u(s_t)] - \mu_f(u)| \leq N\rho^t w(s) \text{ for all } s \in S \text{ and } t \geq 0 \quad (\text{A.16})$$

where

$$\mu_f(u) := \int_S u(y) \mu_f(dy) \quad (\text{A.17})$$

N, ρ are constants independent of f with $N > \rho$, $0 < \rho < 1$. For verification of Assumption A.3, new sufficient conditions are defined.

Lemma A.3. Let the function w satisfy Assumption A.1. With Assumptions A.1 and A.2, following conditions warrants to verify Assumption A.3.

(a) For $f \in F$, there is μ_f , (depending on f), satisfying

$$\sum_{t=0}^{\infty} \rho^t \|P_f^t(\cdot|s) - \mu_f(\cdot)\|_w \leq Nw(s) + m' \text{ for all } s \in S. \quad (\text{A.18})$$

where

$$\|P_f^t(\cdot|s) - \mu_f(\cdot)\|_w := \sup_{|u| \leq w} |E_s^f[u(s_t)] - \mu_f(u)| \quad (\text{A.19})$$

and $N > 0$, $\rho > 1$, and $m' \geq 0$.

(b) $S = [0, \infty)^d$, $d \geq 1$, should be met together with conditions given below.

(i) $P(\cdot|s, f(s))$ is monotone; with $s_t, f \in F$.

(ii) w ; non-decreasing, satisfying

$$\int_s w(y) P(dy|s, f(s)) \leq \beta w(s) + m l_{\{0\}}(s) \text{ for } f \in F, s \geq 0 \quad (\text{A.20})$$

l_D is indicator function of set D .

(c) For $f \in F$, there is c_f (depending on f , in $B(S)$ with $P(\cdot|s, f(s)) = P(\cdot|c_f)$ is independent of $s \in c_f$) and constants, $\delta_1, m_1 \geq 0$, and $\beta_1, 0 < \beta_1 \leq 1$, independent of f , such that

$$\begin{aligned} P(c_f|c_f) &\geq \delta_1 \\ \int_s w(y)P(dy|s, f(s)) &\leq \beta_1 w(s) + m_1 l_{c_f}(s) \text{ for all } s \in S \end{aligned} \quad (\text{A.21})$$

Proof (a) Since $|c(s, a)| \leq Mw(s)$, $w(s) \geq 1$, with Lemma A.3(c) and Equation A.20, $s \in S$ and $\alpha, 0 < \alpha < 1$,

$$\begin{aligned} |h_\alpha(s)| &= E_s^{f_\alpha^*}[\sum_{t=0}^{\infty} \alpha^t c(s_t, f_\alpha^*(s_t))] - E_{s_0}^{f_\alpha^*}[\sum_{t=0}^{\infty} \alpha^t c(s_t, f_\alpha^*(s_t))] \\ &\leq [\sum_{t=0}^{\infty} \alpha^t |E_s^{f_\alpha^*}[c(s_t, f_\alpha^*(s_t))] - E_{s_0}^{f_\alpha^*}[c(s_t, f_\alpha^*(s_t))]|] \\ &= M[\sum_{t=0}^{\infty} r^t |E_s^{f_\alpha^*}[\frac{c(s_t, f_\alpha^*(s_t))}{M}] - E_{s_0}^{f_\alpha^*}[\frac{c(s_t, f_\alpha^*(s_t))}{M}]|] \\ &\leq MN(1 + w(s_0) + \frac{2m'}{N})w(s) \\ &= v_2(s) \end{aligned} \quad (\text{A.22})$$

which yields Assumption A.3 with $v_1(s) = -MN(1 + w(s_0) + 2m'/N)w(s)$.

(b) For $s \in S, f \in F$, and r with $1 < r \leq \beta^{-1}$

$$\sum_{t=0}^{\infty} r^t \|P_f^t(\cdot|s) - \mu f(\cdot)\|_w \leq \frac{2}{1 - \beta r} [w(s) + \frac{m}{1 - \beta}] \quad (\text{A.23})$$

which together with (a), yields to Assumption A.3.

In the thesis; it is shown that for $w(s)$, κ is available satisfying;

$$\begin{aligned} \frac{w(s) + 1}{w(s)} &\leq \kappa < \infty \\ \sum_{\hat{s} \in S} w(\hat{s}) P(\hat{s}|s, a) &\leq \kappa w(s) \\ \sum_{\hat{s} \in S} w(\hat{s}) P_d(\hat{s}|s, a) &\leq w(s) + 1 \leq (1 + 1)w(s) \\ \alpha^N \sum_{\hat{s} \in S} w(\hat{s}) P_d^N(\hat{s}|s, a) &\leq \alpha^N (w(s) + N) \leq (1 + N)w(s) \end{aligned} \quad (\text{A.24})$$

with $\pi \in \Pi^{MD}$ indicating Markovian deterministic policy sets $s \in S$. For an $\alpha, 0 \leq \alpha < 1$, there is a $\beta, 0 \leq \beta < 1$, integer N satisfying [53];

$$\alpha^N \Sigma_{\hat{s} \in S} P_d^N(\hat{s}|s, a) \leq \beta w(s) \quad (\text{A.25})$$

for $\pi = (\pi_1, \dots, \pi_N)$, where $\pi_k \in \Pi^{MD}, 1 \leq k \leq N$. For all values within $\pi \in \Pi^{MD}$;

$$|V_\alpha(s)| \leq \frac{1}{1-\beta} [1 + \alpha\kappa + \dots + (\alpha\kappa)^{(N-1)}] w(s) \quad (\text{A.26})$$

This verifies the satisfaction of the third condition (Assumption A.3). Thus, with the verification of all the tree conditions (Assumptions A.1, A.2, and A.3), the Theorem 1 has been proved.

Appendix B

Proof of Theorem 2

The studies in this thesis are based on an optimal policy that is treated by MDP. Optimal policy is assumed to be switching type.

B.1 Theorem 2

Theorem 2: π^* , optimal policy, is switching type. If a, b are arbitrary actions of set $\{0, \lfloor \frac{2^R N}{2^{R+1}} \rfloor, \lfloor \frac{2^R N}{2^{R+1}} \rfloor + 1, \dots, N\}$,

- If $\pi^*((\Delta_1, \Delta_2)) = a$, $\pi^*((\Delta_1, \Delta_2 + n)) = b$, $b \geq a$,
- If $\pi^*((\Delta_1, \Delta_2)) = a$, $\pi^*((\Delta_1 + n, \Delta_2)) = b$, $b \leq a$,

where n ; a positive integer.

B.2 Switching Type Policy

There are conditions for being a switching type policy. These conditions are studied by and [53], and [80]-[83]. For the completeness of the thesis, the referenced studies are adapted to the Theorem 2 which is stated in the main body of the thesis.

A switching type policy is monotone policy (non-decreasing/non-increasing). We need to introduce a Lemma to use in proofing process.

Lemma B.1

For $\Pi = (\pi_1, \pi_2, \dots, \pi_N)$ and π_∞ are Markov policies for a finite and infinite horizon models; $v_i^N(\Pi) = v_{(i,1)}(\pi_\infty)$ for $i \in S$.

Proof

It can shown that, by induction on n , for i, j, n

$$\begin{aligned} \{[P^*(\pi)]^{n-1}\}_{(i,1)(j,n)} &= \{P(\pi_1)P(\pi_2)\dots P(\pi_{n-1})\}_{ij} \\ \pi_{(j,n)}^*(\pi) &= \pi_j(\pi) \\ \Sigma_j \{[P^*(\pi)]^N\}_{(i,j)(j,N+1)} &= 1 \\ \pi_{(j,N+1)}^*(\pi) &= 0 \end{aligned} \tag{B.1}$$

$n \leq N$. Therefore,

$$\begin{aligned} v_{i,1}(\pi_\infty) &= \Sigma_{n=1}^\infty \{[P^*(\pi)]^{n-1} \pi^* \pi\}_{(i,1)} = \Sigma_{n=1}^N \{[P^*(\pi)]^{n-1} \pi^* \pi\}_{(i,1)} \\ &= \Sigma_{n=1}^N \Sigma_{j \in S} \{[P^*(\pi)]^{n-1}\}_{(i,1)(j,n)} \pi_{(j,n)}^*(\pi) \\ &= \Sigma_{n=1}^N \Sigma_{j \in S} [P(\pi_1)P(\pi_2)\dots P(\pi_{n-1})]_{i,j} \pi_j(\pi_n) \\ &= \Sigma_{n=1}^N \{[P(\pi_1)P(\pi_2)\dots P(\pi_{n-1})]\pi(\pi_n)\}_i = v_i^N(\Pi), i \in S \end{aligned} \tag{B.2}$$

For Monotone policy optimality, we need following lemma.

Lemma B.2

Assume $y, z : S \rightarrow \Pi_+$ satisfies $\Sigma_{j=k}^N y_j \geq \Sigma_{j=k}^N z_j$, $2 \leq k \leq N$ $\Sigma_{j=1}^N y_j = \Sigma_{j=1}^N z_j$,

Assume $v : S \rightarrow \Pi$ satisfies $v_{j+1} \geq v_j$, with $j = 1, 2, \dots, N-1$

We reach $\Sigma_{j=1}^N v_j y_j \geq \Sigma_{j=1}^N v_j z_j$.

Proof

Define $v_0 = 0$. Then,

$$\begin{aligned}
\Sigma_{j=1}^N v_j y_j &= \Sigma_{j=1}^N y_j \{ \Sigma_{k=1}^j (v_k - v_{k-1}) \} \\
&= \Sigma_{k=1}^N (v_k - v_{k-1}) \{ \Sigma_{j=k}^N y_j \} \\
&= v_1 \Sigma_{j=1}^N y_j + \Sigma_{k=2}^N (v_k - v_{k-1}) \{ \Sigma_{j=k}^N y_j \} \\
&= v_1 \Sigma_{j=1}^N z_j + \Sigma_{k=2}^N (v_k - v_{k-1}) \{ \Sigma_{j=k}^N z_j \} = \Sigma_{j=1}^N v_j z_j
\end{aligned} \tag{B.3}$$

Assume X and Y are sequential sets, $f(x, y)$ on XY . Function f is considered as *super-additive*, $(x_1, x_2) \in Y$, $x_1 \geq x_2$, $y_1 \geq y_2$, satisfies;

$$f(x_1, y_1) + f(x_2, y_2) \geq f(x_1, y_2) + f(x_2, y_1). \tag{B.4}$$

When opposite inequality is observed; for $x_1, x_2 \in X$, $(x_1 \geq x_2)$, $(y_1 \geq y_2)$

$$f(x_1, y_1) + f(x_2, y_2) \leq f(x_1, y_2) + f(x_2, y_1) \tag{B.5}$$

f ; a *sub-modular* or *sub-additive* function.

B.3 Monotone Optimal Policy

$f^\infty \in C(D)$ is said to be a *policy of monotone type* when we verify;

$$\begin{aligned}
f(i+1) &\geq f(i) \quad \text{with } i = 1, 2, \dots, N-1 \text{ (non-decreasing)} \\
f(i+1) &\leq f(i) \quad \text{with } i = 1, 2, \dots, N-1 \text{ (non-increasing)}
\end{aligned} \tag{B.6}$$

Existence of monotone policy is verified with following assumptions:

Assumption B.1

- (a) Reward/cost function $r_i(a)$ is non-decreasing.
- (b) $\Sigma_{j=k}^N p_{ij}(a)$ is nondecreasing in i , where $p_{ij}(a)$ is transition probability given in Equations 3.19-3.30.
- (c) $r_i(a)$ is super-modular (super-additive) or sub-modular (sub-additive) on SxA .
- (d) $q_k = \Sigma_{j=k}^N p_{ij}(a)$ is super-modular (super-additive) on SxA for all k .

Proof is done by value iteration method, $v^n = Uv^{n-1}$, with $v^0 = 0$ and $n=1,2,\dots$. Taking limit yields; $\lim_{n \rightarrow \infty} v^n = v^\alpha$.

Lemma B.2

With Assumptions B.1(a) and B.1(b), v_i^n is non-decreasing in i with $n=0,1,\dots$

Proof

Proof is done by using induction with n . If $n = 0$, $v_i^n = 0$ for all $i \in S$; results are correct. Suppose that results are correct also for n . Assumption B.1(b), $\sum_{j=k}^N p_{i+1,j}(a) \geq \sum_{j=k}^N p_{i,j}(a)$ at all values of k, a ; $\sum_{j=1}^N p_{i+1,j}(a) = \sum_{j=1}^N p_{i,j}(a) = 1$, using Lemma B.1

$$\sum_{j=1}^N p_{i+1,j}(a) v_j^n = \sum_{j=1}^N p_{i,j}(a) v_j^n \quad (\text{B.7})$$

at all nondecreasing values of i and all a .

Using B.1(a);

$$r_{i+1}(a) + a \cdot \sum_{j=1}^N p_{i+1,j}(a) v_j^n \geq r_i(a) + a \cdot \sum_{j=1}^N p_{i,j}(a) v_j^n \quad (\text{B.8})$$

at nondecreasing values of i, a .

Hence,

$$\begin{aligned} v_{i+1}^{n+1} &= \max_a \{r_{i+1}(a) + a \cdot \sum_{j=1}^N p_{i+1,j}(a) v_j^n\} \\ &\geq \max_a \{r_i(a) + a \cdot \sum_{j=1}^N p_{i,j}(a) v_j^n\} \\ &= v_i^{n+1} \end{aligned} \quad (\text{B.9})$$

at all nondecreasing values of i , v_i^a is non-decreasing.

Corollary B.1

Under the Assumptions B.1(a), B.1(b), v_i^a is nondecreasing in i .

Proof

It is required to show; $s_i(a) := r_i(a) + a \cdot \sum_{j=1}^N p_{i,j}(a) v_j^a$ is super-modular on $Sx A$.

Assume $a_1 \geq a_2$, $i_1 \geq i_2$, $y_j := p_{i_1 j}(a_1) + p_{i_2 j}(a_2)$, $z_j := p_{i_1 j}(a_2) + p_{i_2 j}(a_1)$ at all values of $j \in S$. Using Assumption B.1(d) with $1 \leq k \leq N$; $\sum_{j=1}^N y_j \geq \sum_{j=k}^N z_j$. Since $\sum_{j=1}^N y_j = \sum_{j=1}^N z_j = 2$, and because v_i^a is non-decreasing in i (see corollary B.1), applying Lemma B.2 yields

$$\sum_{j=1}^N \{p_{i_1 j}(a_1) + p_{i_2 j}(a_2)\} v_j^a \geq \sum_{j=1}^N \{p_{i_1 j}(a_2) + p_{i_2 j}(a_1)\} v_j^a \quad (\text{B.10})$$

i.e. $\sum_{j=1}^N p_{ij}(a) v_j^a$ is subadditive, in turn, $s_i(a)$ is subadditive as well for $Sx A$.

B.4 Proof of Theorem 2 for the Thesis

The policy is switching type, i.e. monotone non-decreasing in Δ_2 if Δ_1 is constant, and monotone non-increasing in Δ_1 if Δ_2 is constant. Optimal monotone policy existence proof requires satisfying conditions of Assumption B.1(a)-B.1(d).

The current state is $s_t = (\Delta_1, \Delta_2)$. When Δ_1 is fixed, the new state is $s_{t+1}(\Delta_1, \Delta_2 + n)$, n is positive integer. When Δ_2 is fixed, the new state is $s_{t+1}(\Delta_1 + n, \Delta_2)$. For state s_t , the reward function r_t for all actions $a_t, a_t \in A$ is

$$r_t(a) = r(s_t, a_t) = w(s_t) = w_1(\Delta_{1,t}) + w_2(\Delta_{2,t}) \quad (\text{B.11})$$

For state s_{t+1} , reward function r_{t+1} when $\Delta_{1,t}$ is fixed, for all actions $a_t \in A$, is defined as

$$r_{t+1}(a_{t+1}) = r(s_{t+1}, a) = w_1(\Delta_{1,t}) + w_2(\Delta_{2,t} + n) \quad (\text{B.12})$$

For state s_{t+1} , reward function r_{t+1} when $\Delta_{2,t}$ is fixed, for all actions $a_t \in A$, is defined as

$$r_{t+1}(a) = r(s_{t+1}, a_{t+1}) = w_1(\Delta_{1,t} + n) + w_2(\Delta_{2,t}) \quad (\text{B.13})$$

Assumption B.1(a):

Reward function $r(s_t, a_t)$ is non-decreasing if $(\Delta_{2,t} + n) \geq \Delta_{2,t}$ for fixed $\Delta_{1,t}$, or $(\Delta_{1,t} + n) \geq \Delta_{1,t}$ for constant $\Delta_{2,t}$. Because n is a positive integer, $r_{t+1} \geq r_t$. It is obvious that the condition (Assumption B.1(a)) holds.

Assumption B.1(b):

Transition probability for s_t to s_{t+1} transition, $P(s_{t+1}|s_t, a_t)$, with a_t where $a_t \in A_{\text{OMA,NOMA}} \cup A_{\text{RSMA}}$. By using users' outage probabilities with selections of RSMA, OMA or NOMA, we have the transition probabilities expressed in Equations (3.19)-(3.30). If current state $s_t = s_1 = (\Delta_{1,t}, \Delta_{2,t}) = (\Delta_1, \Delta_2)$, the next possible states are $s_1 = [(1, \Delta_2 + 1), (\Delta_1 + 1, \Delta_2 + 1)]$, $s_2 = [(1, 1), (\Delta_1 + 1, 1)]$. Based on these equations, using induction:

$$\begin{aligned} q(k|s_t, a_t = 0) &= 1 \quad \text{when } k \leq s_1 \\ &= 0 \quad \text{when } k > s_1 \end{aligned} \quad (\text{B.14})$$

$$\begin{aligned}
q(k|s_t, a_t = i), 0 < i < N = 1 & \quad \text{when } k \leq s_2 \\
= 0 & \quad \text{when } k > s_1 \\
= P_2^{NOMA}(i) & \quad \text{when } s_1 \geq k > s_2
\end{aligned} \tag{B.15}$$

$$\begin{aligned}
q(k|s_t, a_t = i, \alpha_c), 0 < i < N = 0 & \quad \text{when } k > s_1, \alpha_c \neq 0 \\
= P_2^{RSM A}(i) & \quad \text{when } s_1 \geq k > s_2 \\
= 1 & \quad \text{when } k \leq s_2, \alpha_c \neq 0
\end{aligned} \tag{B.16}$$

$$\begin{aligned}
q(k|s_t, a_t = N) = 0 & \quad \text{when } k > s_1 \\
= P_2^{OMA} & \quad \text{when } s_1 \geq k > s_2 \\
= 1 & \quad \text{when } k \leq s_2
\end{aligned} \tag{B.17}$$

So that, the condition (Assumption B.1(b)) holds.

Assumption B.1(c):

Assume X, Y are sequential, function $f(x, y)$ on $X \times Y$. f is *super-modular* (*super-additive*) when; $x_1, x_2 \in Y, x_1 \geq x_2, y_1 \geq y_2$,

$$f(x_1, y_1) + f(x_2, y_2) \geq f(x_1, y_2) + f(x_2, y_1). \tag{B.18}$$

When reverse inequality occurs; for $x_1, x_2 \in X, x_1 \geq x_2, y_1 \geq y_2$,

$$f(x_1, y_1) + f(x_2, y_2) \leq f(x_1, y_2) + f(x_2, y_1). \tag{B.19}$$

Function f is called *sub-modular* or *sub-additive*

The multi-variable reward $r(s_t, a_t) : S \times A \rightarrow \Pi$ is sub-additive in (s_t, a_t) , if for all $s_{t+1} \leq s_t$ and $a_{t+1} \leq a_t$,

$$r(s_{t+1}, a_{t+1}) + r(s_t, a_t) \leq r(s_{t+1}, a_t) + r(s_t, a_{t+1}) \tag{B.20}$$

holds. The condition (Assumption B.1(c)) is satisfied with $r(s_t, a_t)$ given in Equation B.10.

Assumption B.1(d):

To verify the last condition (Assumption B.1(d)), we should check whether the following condition is verified,

$$q(k|s_{t+1}, a_{t+1}) + q(k|s_t, a_t) \leq q(k|s_{t+1}, a_t) + q(k|s_t, a_{t+1}) \tag{B.21}$$

with $s_{t+1} = (\Delta_{1,t}, \Delta_{2,t+1})$, and $s_t = (\Delta_{1,t}, \Delta_{2,t})$ where $\Delta_{2,t+1} \geq \Delta_{2,t}$ and $a_{t+1} \geq a_t$. There are four actions with the possible four cases given below. (1)

$a_{t+1} = i, a_t = 0$, (2) $a_{t+1} = N, a_t = 0$, (3) $a_{t+1} = N, a_t = i$, (4) $a_{t+1} = i, a_t = j$ for $0 \leq j \leq i \leq N$

When we apply the cases mentioned above in Equations B.14-B.17, we see that the condition defined in Equation B.21, is verified for all the cases. This shows that the fourth condition (Assumption B.1(d)) is verified. Since all the conditions are correct, policy is non-decreasing in Δ_2 , when Δ_1 is fixed. Proof of policy in Δ_1 can be made by using similar steps in a switching way.

Appendix C

Additional Adaptive Policy Graphics

C.1 Additional Adaptive Policy Graphics for Equal Common Target Rates

The adaptive RSMA/NOMA/OMA policy related to the Table 5.2 and Table 5.3 are indicated in Figure 5.1- Figure C.9 and Figure 5.7 as 2-D colored graphs. These colored graphs show the results only for transmission SNR, $\rho = 18$ dB. The results for the transmission SNR, $\rho = 20$ dB are given here in Figure C.1 - Figure C.9. Regarding the percentage of the colored areas indicating OMA, NOMA, and RSMA, the adaptive policy takes the actions for OMA, NOMA, and RSMA in all of the actions with the percentages indicated in Table C.1.

Table C.1 shows that RSMA outperforms RSMA/NOMA/OMA above the threshold value of $\lambda_c = 0.15$ for the user distances to BS $d_1 = 2$, $d_2 = 4$, while NOMA/OMA dominates when $\lambda_c \leq 0.15$. This threshold value decreases with increasing user distances to the BS.

Table C.1: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with equal common target rates when $d_2/d_1 = 2$, SNR=20 dB

Policy for all actions, %						
$\lambda_{c,1} = \lambda_{c,2}$	$d_1 = 2, d_2 = 4$			$d_1 = 3, d_2 = 6$		
	OMA	NOMA	RSMA	OMA	NOMA	RSMA
0.10	8	92	0	27	73	0
0.13	8	92	0	22	4	74
0.14	8	92	0	20	0	80
0.15	8	87	5	26	0	84
0.16	8	87	5	12	0	88
0.17	8	38	54	9	0	91
0.18	6	10	84	8	0	92
0.19	5	7	88	5	0	95

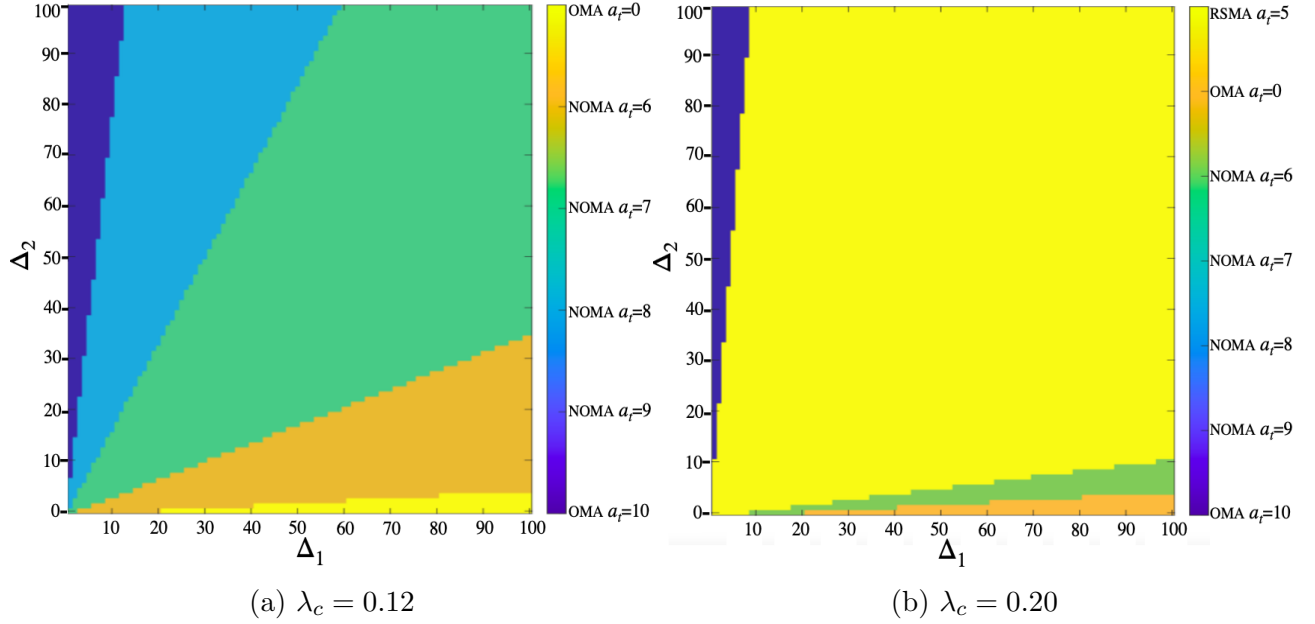


Figure C.1: Adaptive policy with equal common target rates when $\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.12, 0.20$, $[d_1 = 2, d_2 = 4]$, $\rho = 20$ dB

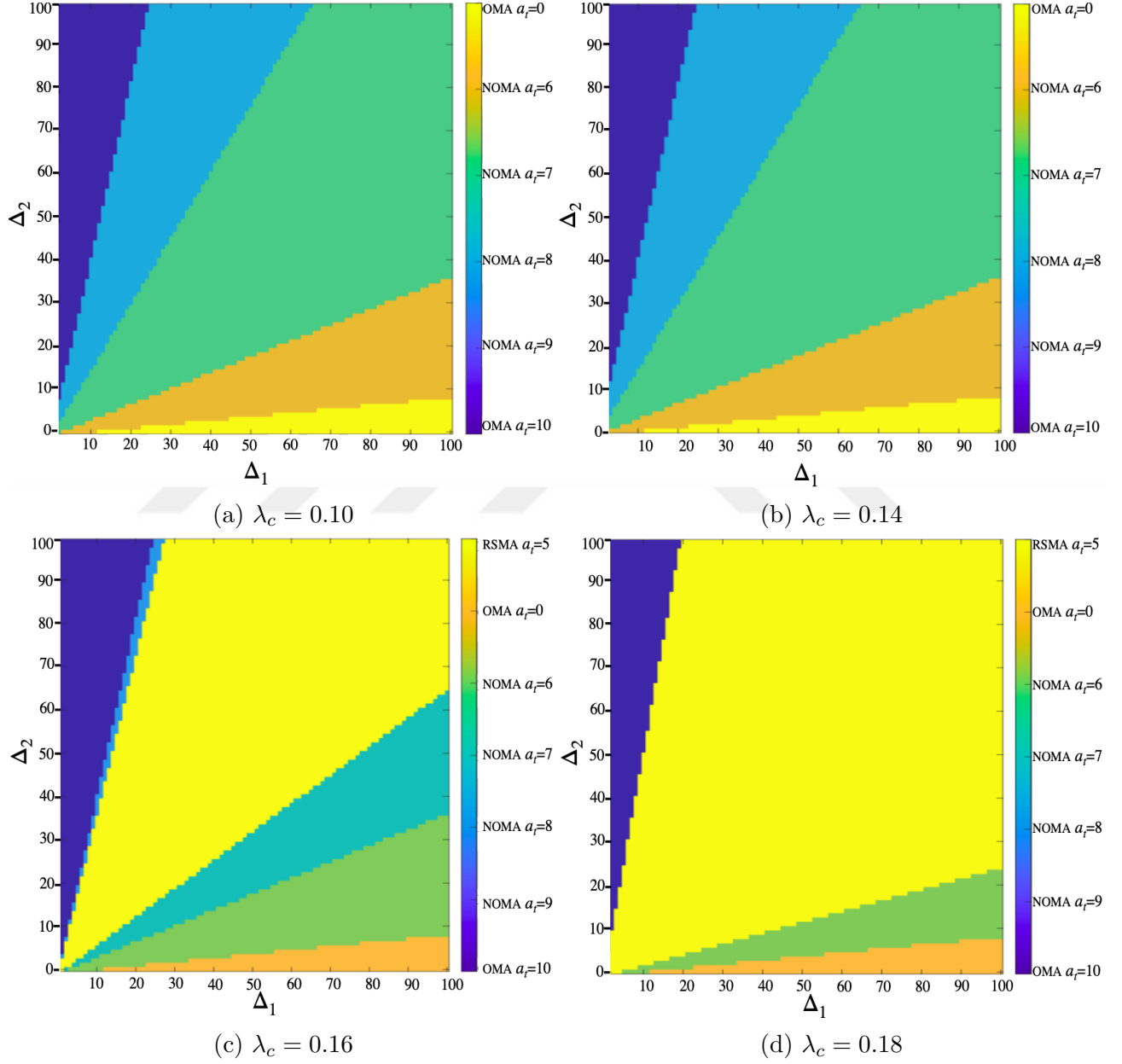


Figure C.2: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.10, 0.14, 0.16, 0.18$), $[d_1 = 2, d_2 = 4]$, $\rho = 18$ dB, equal target rates and user weights

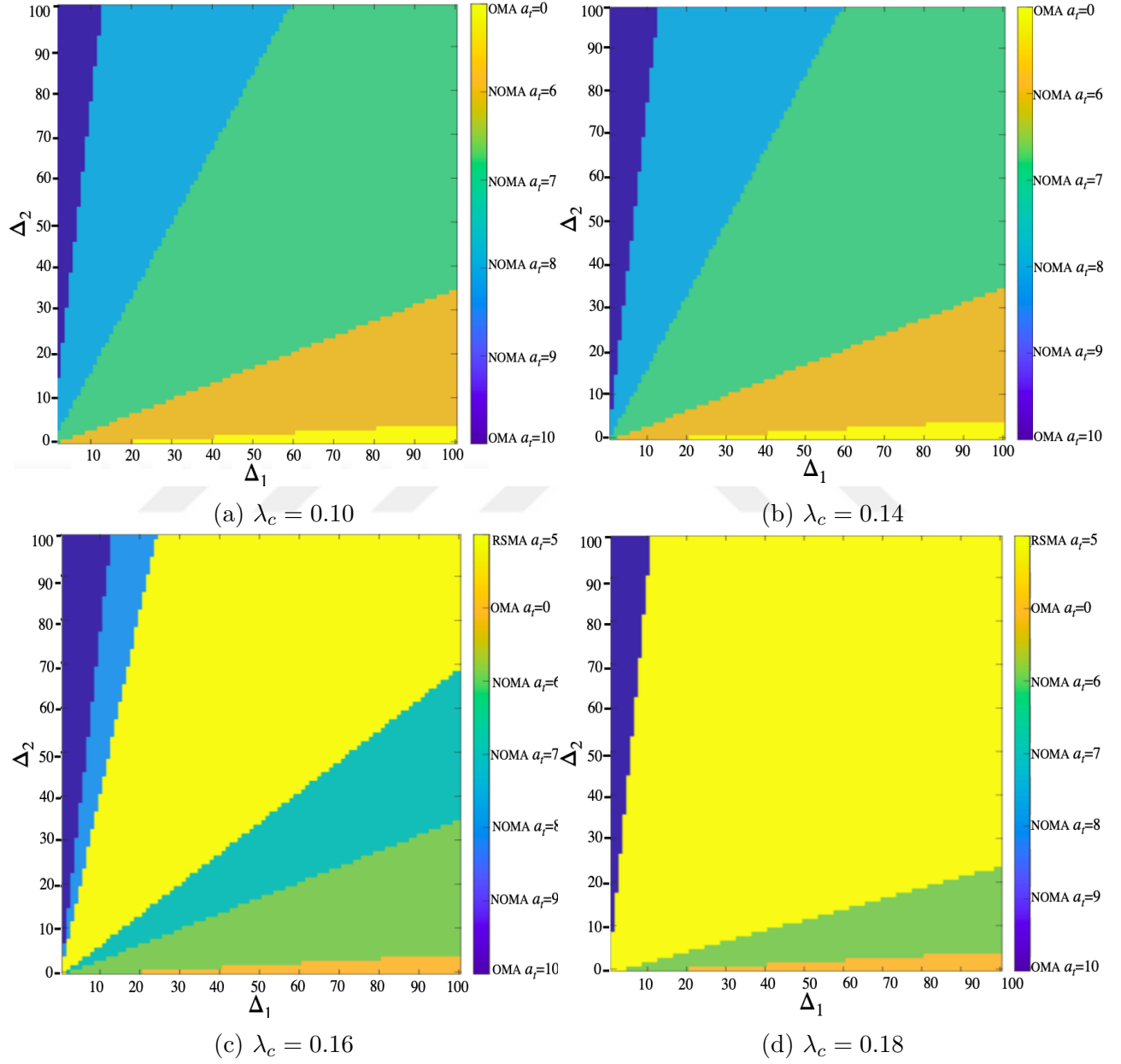


Figure C.3: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.10, 0.14, 0.16, 0.18$), $[d_1 = 2, d_2 = 4]$, $\rho = 20$ dB, equal target rates and user weights

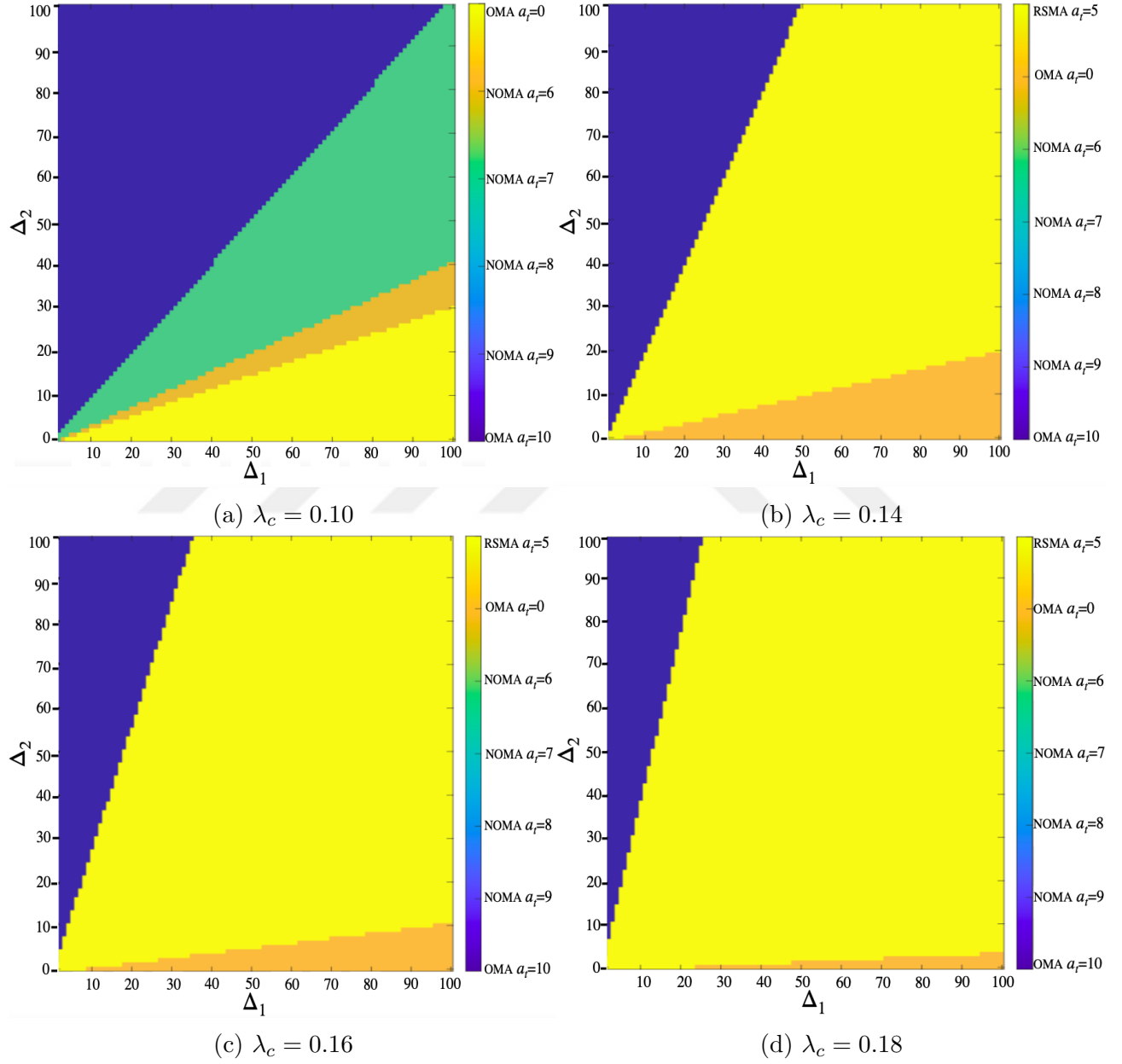


Figure C.4: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.10, 0.14, 0.16, 0.18$), $[d_1 = 3, d_2 = 6]$, $\rho = 18$ dB, equal target rates and user weights

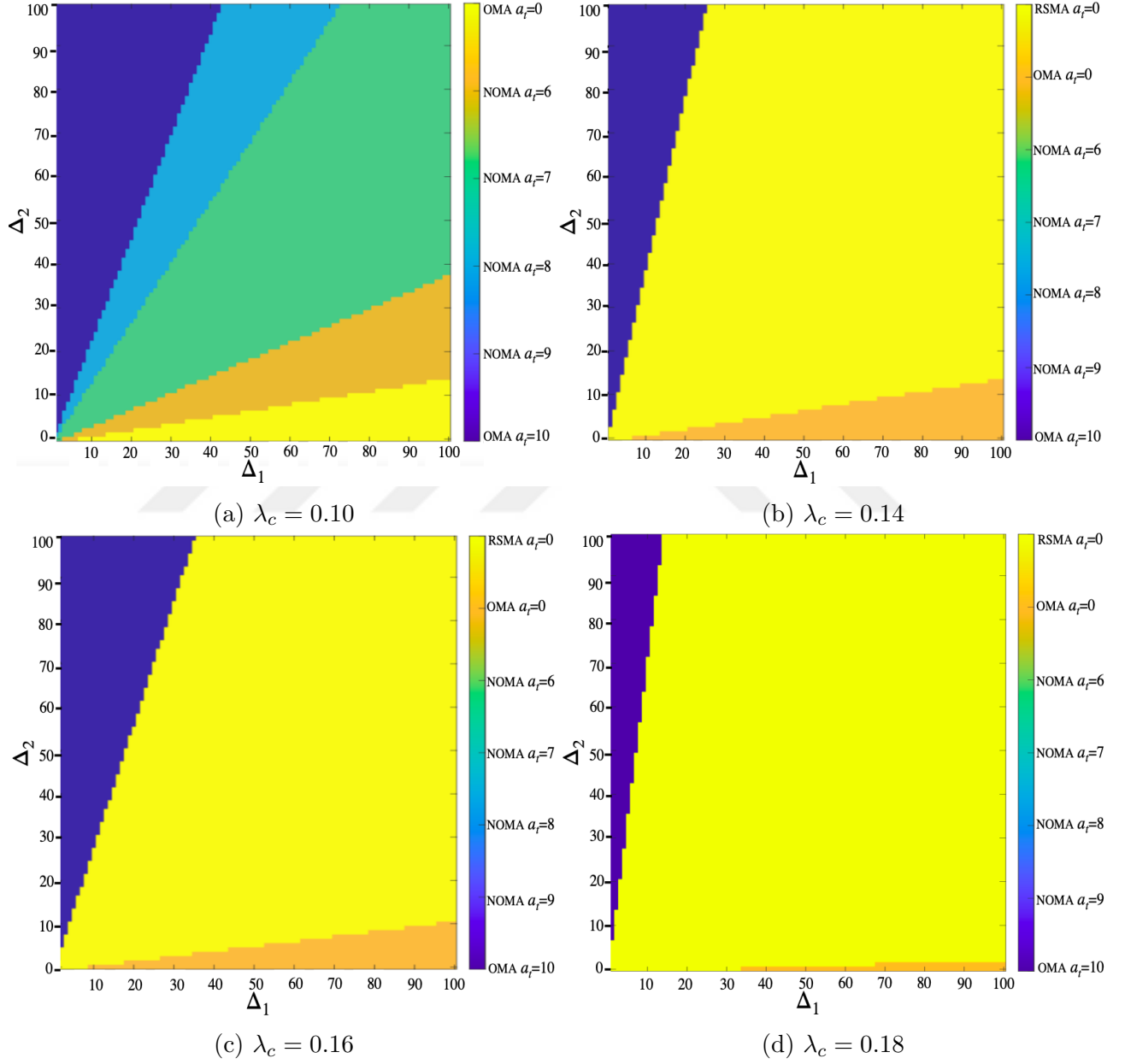


Figure C.5: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.10, 0.14, 0.16, 0.18$), $[d_1 = 3, d_2 = 6]$, $\rho = 20$ dB, equal target rates and user weights

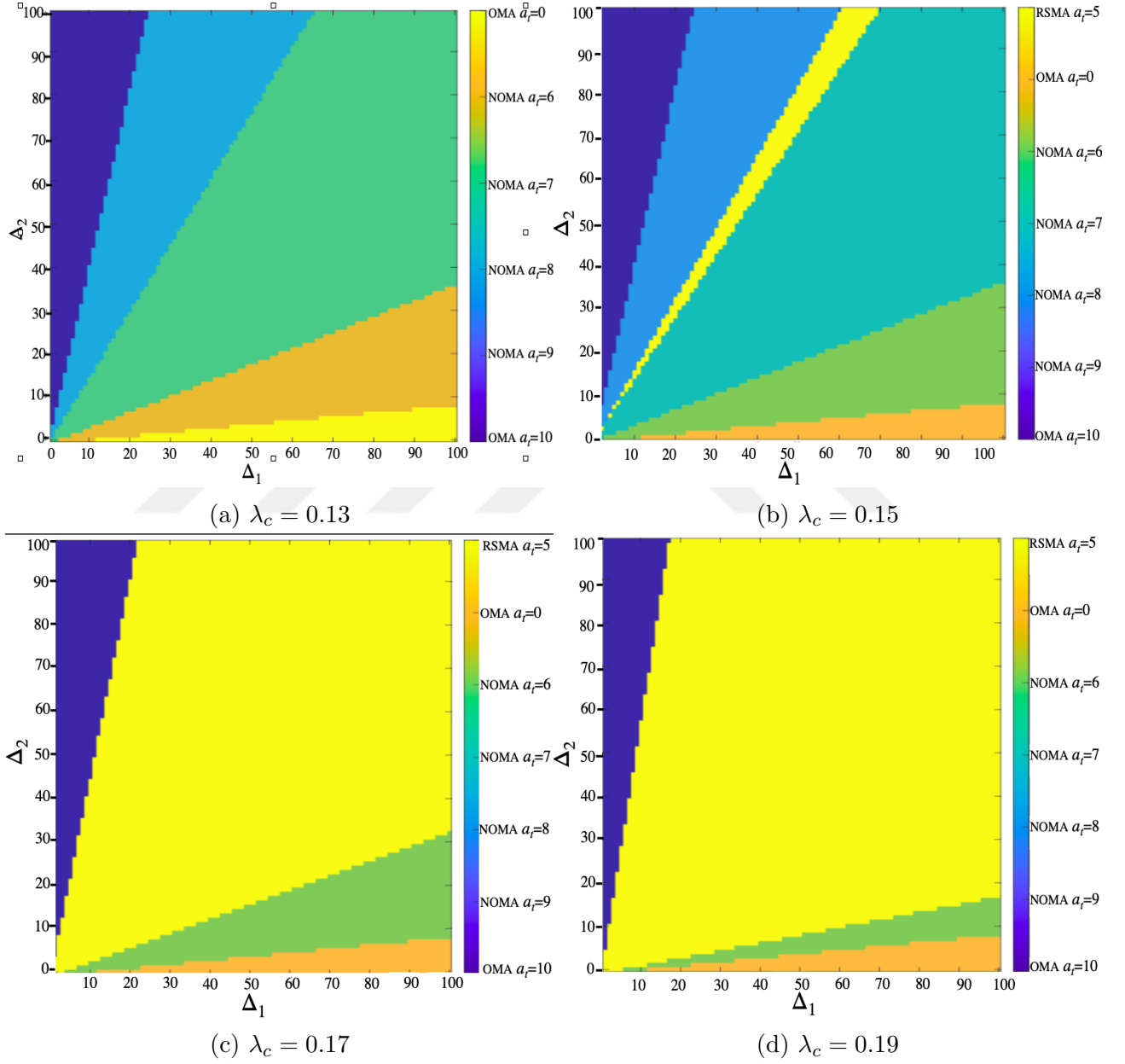


Figure C.6: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.13, 0.15, 0.17, 0.19$), $[d_1 = 2, d_2 = 4]$, $\rho = 18$ dB, equal target rates and user weights

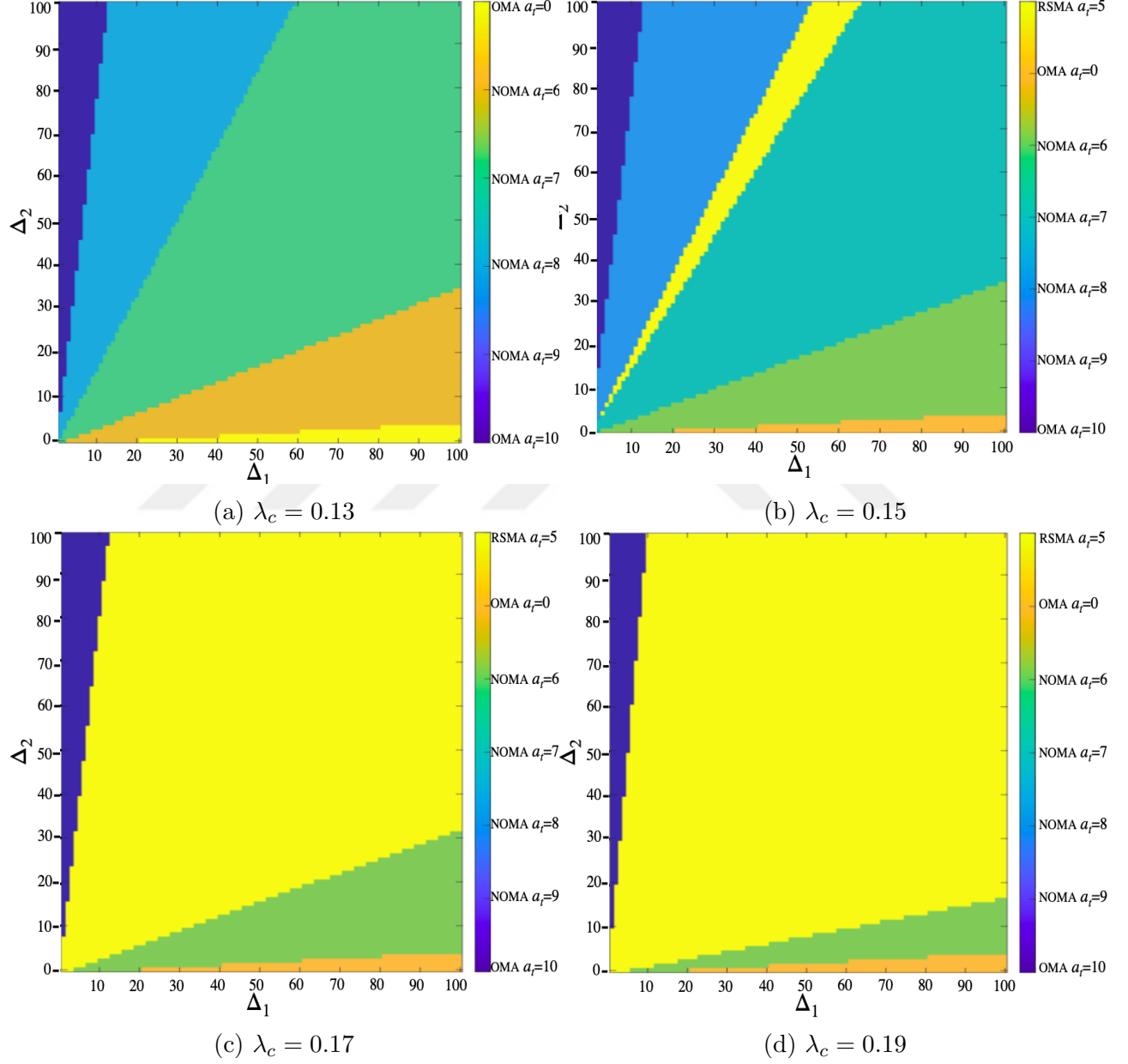


Figure C.7: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.13, 0.15, 0.17, 0.19$), $[d_1 = 2, d_2 = 4]$, $\rho = 20$ dB, equal target rates and user weights

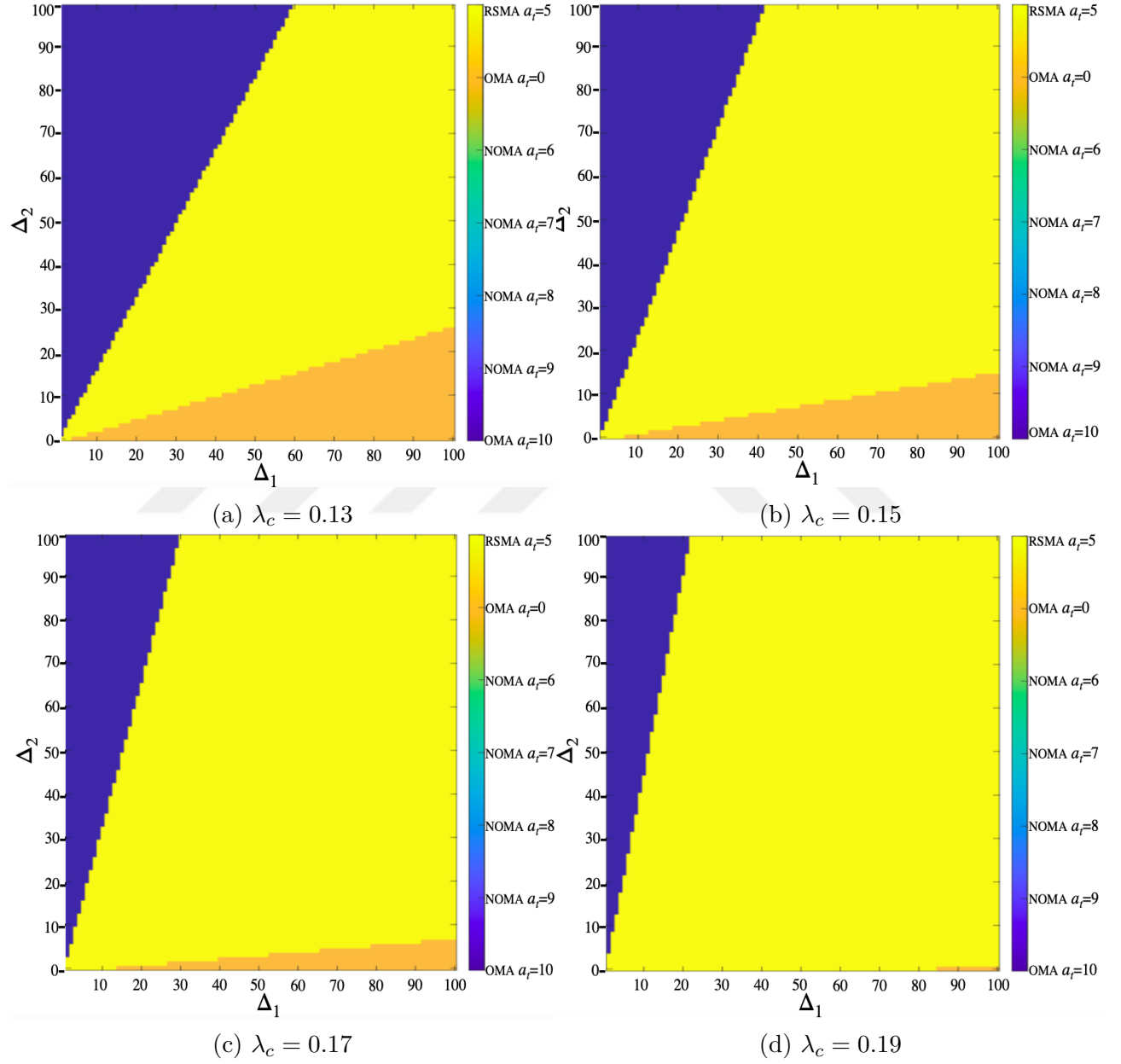


Figure C.8: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.13, 0.15, 0.17, 0.19$), $[d_1 = 3, d_2 = 6]$, $\rho = 18$ dB, equal target rates and user weights

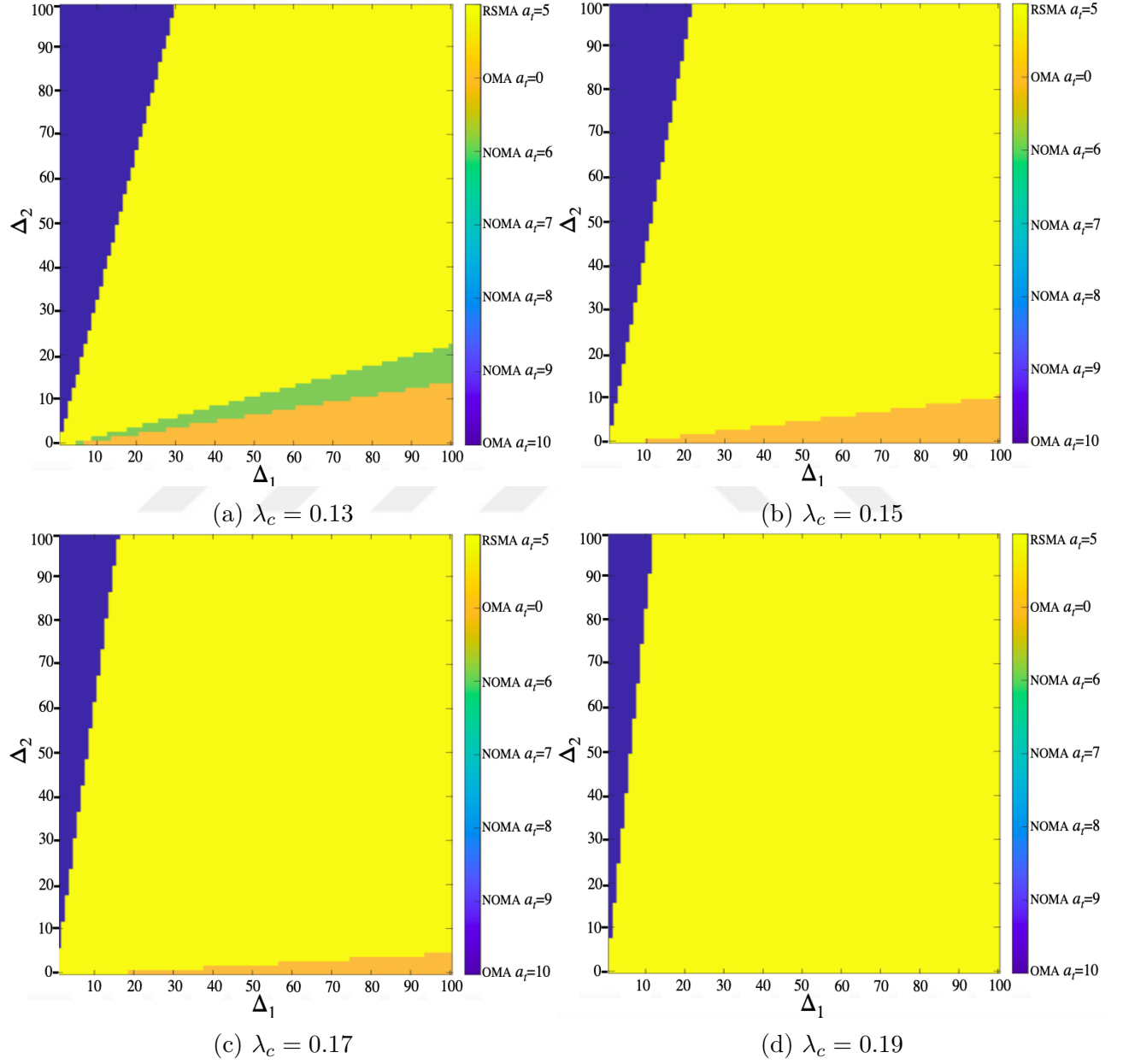


Figure C.9: Adaptive policy with equal common target rates ($\lambda_{c,1} = \lambda_{c,2} = \lambda_c = 0.13, 0.15, 0.17, 0.19$), $[d_1 = 3, d_2 = 6]$, $\rho = 20$ dB, equal target rates and user weights

C.2 Additional Adaptive Policy Graphics for Unequal Common Target Rates

The adaptive RSMA/NOMA/OMA policy related to the Table 5.6 and Table 5.7 are shown in Figure 5.8 only for four of the cases, two cases with $\lambda_{c,1} > \lambda_{c,2}$ and the other two cases with $\lambda_{c,1} < \lambda_{c,2}$, are given in Chapter 5. In these figures, the transmission SNR $\rho = 18$ dB. The figures for the rest of thirty-two cases for which $\rho = 18$ dB or $\rho = 20$ dB are indicated here in Figure C.10 - Figure C.17. Regarding percentage of the colored areas indicating OMA, NOMA, and RSMA, the adaptive policy takes the actions for OMA, NOMA, and RSMA in all of the actions with the percentages given in Table C.2.

Table C.2 shows that RSMA outperforms RSMA/NOMA/OMA above $\lambda_c = 0.12$. $\lambda_{c,2}$ is more effective in RSMA selection than $\lambda_{c,1}$. For example, comparing the results for (12, 20) with (20, 12) shows that RSMA selection percentages are 64% and 25%, respectively.

C.3 Additional Adaptive Policy Graphics for Unequal User Weights

The adaptive RSMA/NOMA/OMA policy related to the Table 5.8 and Table 5.9 are indicated in Figure 5.9 as 2-D colored graphs for the scenarios where $R_1^* = R_2^* = 1.0$, $\lambda_1 = \lambda_2 = 0.12$ and $\rho = 18$ dB. The figures for other scenarios are indicated here in Figure C.18 - Figure C.20. Regarding percentage of the colored areas indicating OMA, NOMA, and RSMA, above the threshold common target rate, the adaptive policy takes the actions for OMA, NOMA, and RSMA in all of the actions with the percentages shown in Table C.3. When $w_2 > 0.5$ ($w_1 \leq 0.5$), RSMA preference increases with increasing w_1 (decreasing w_2). However, when $w_1 > 0.5$ ($w_2 < 0.5$), RSMA preference decreases with increasing w_1 (decreasing w_2).

Table C.2: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with unequal common target rates

Policy for all actions, %				
$\lambda_{c,1}, \lambda_{c,2}$	ρ (dB)	OMA	NOMA	RSMA
(0.10, 0.18)	18	8	92	0
(0.10, 0.18)	20	8	92	0
(0.10, 0.20)	18	15	71	14
(0.10, 0.20)	20	8	76	16
(0.12, 0.18)	20	6	92	2
(0.12, 0.20)	18	16	21	63
(0.12, 0.20)	20	8	28	64
(0.14, 0.20)	18	17	8	75
(0.14, 0.20)	20	8	15	77
(0.16, 0.20)	18	14	3	83
(0.16, 0.20)	20	8	5	87
(0.18, 0.20)	18	13	2	85
(0.18, 0.20)	20	2	4	94
(0.15, 0.18)	20	8	19	73
(0.18, 0.10)	18	16	84	0
(0.18, 0.10)	20	8	92	0
(0.18, 0.12)	20	8	92	0
(0.18, 0.15)	20	16	29	55
(0.20, 0.10)	18	16	84	0
(0.20, 0.10)	20	8	87	5
(0.20, 0.12)	18	8	67	25
(0.20, 0.12)	20	7	66	27
(0.20, 0.14)	18	12	37	51
(0.20, 0.14)	20	6	38	56
(0.20, 0.16)	18	13	18	69
(0.20, 0.16)	20	6	18	76
(0.20, 0.18)	18	12	8	80
(0.20, 0.18)	20	6	9	85

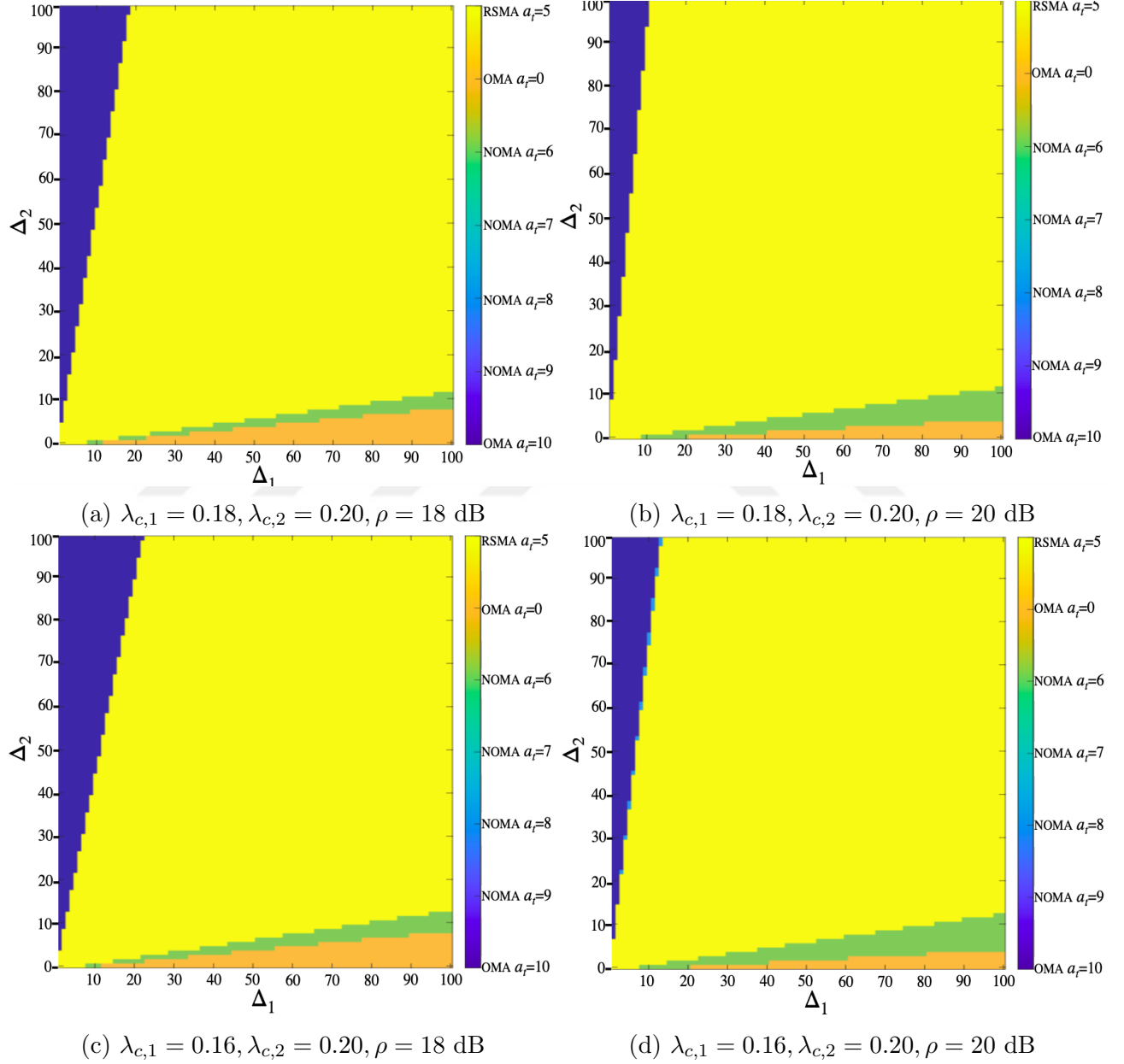


Figure C.10: Adaptive policy with unequal common target rates when $\lambda_{c,2} > \lambda_{c,1}$ [equal target rates and user weights, $\lambda_{c,1} = (0.18, 0.16), \lambda_{c,2} = 0.20$]

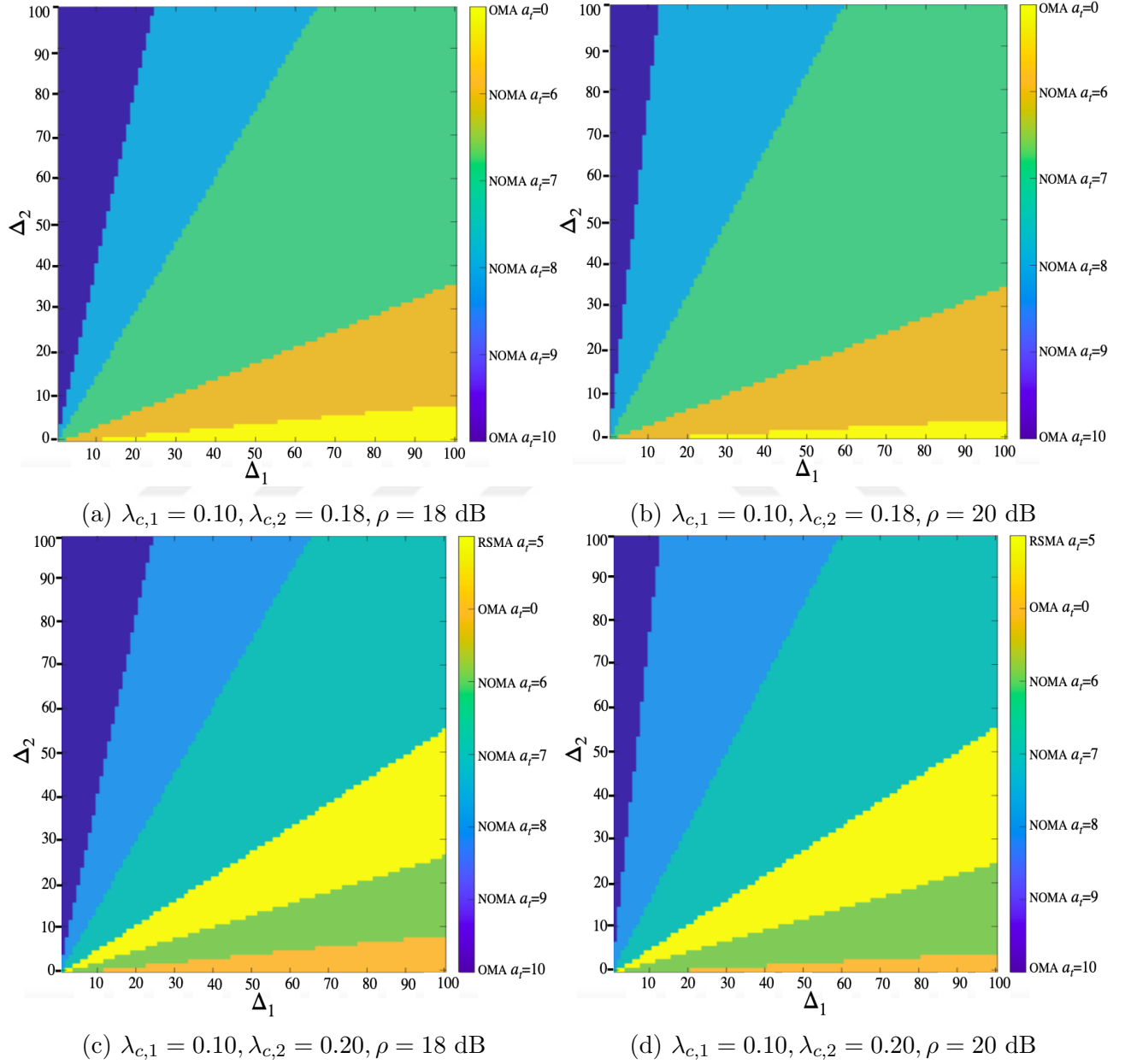


Figure C.11: Adaptive policy with unequal common target rates when $\lambda_{c,2} > \lambda_{c,1}$ [equal target rates and user weights, $\lambda_{c,1} = 0.10, \lambda_{c,2} = (0.18, 0.20)$]

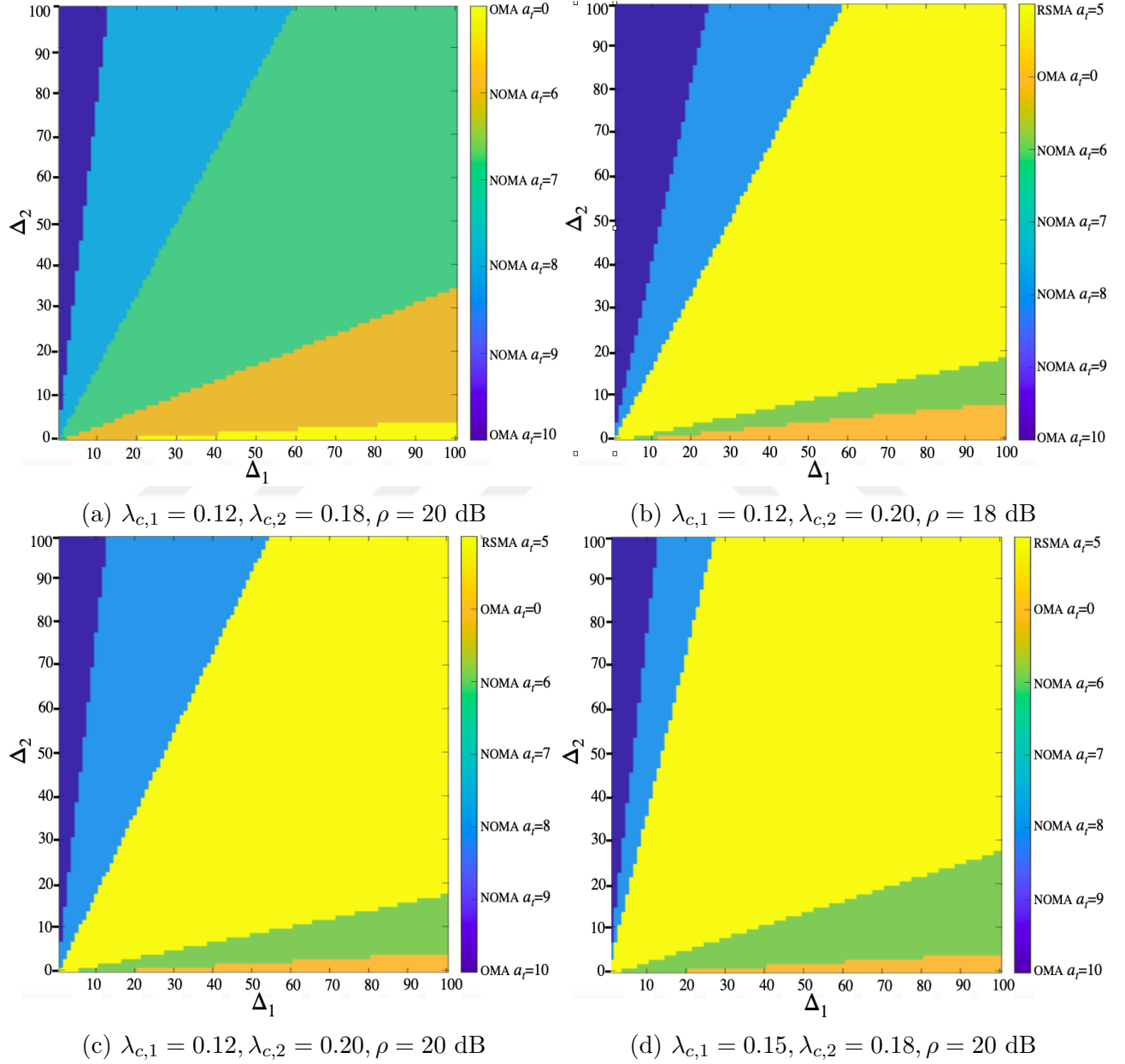
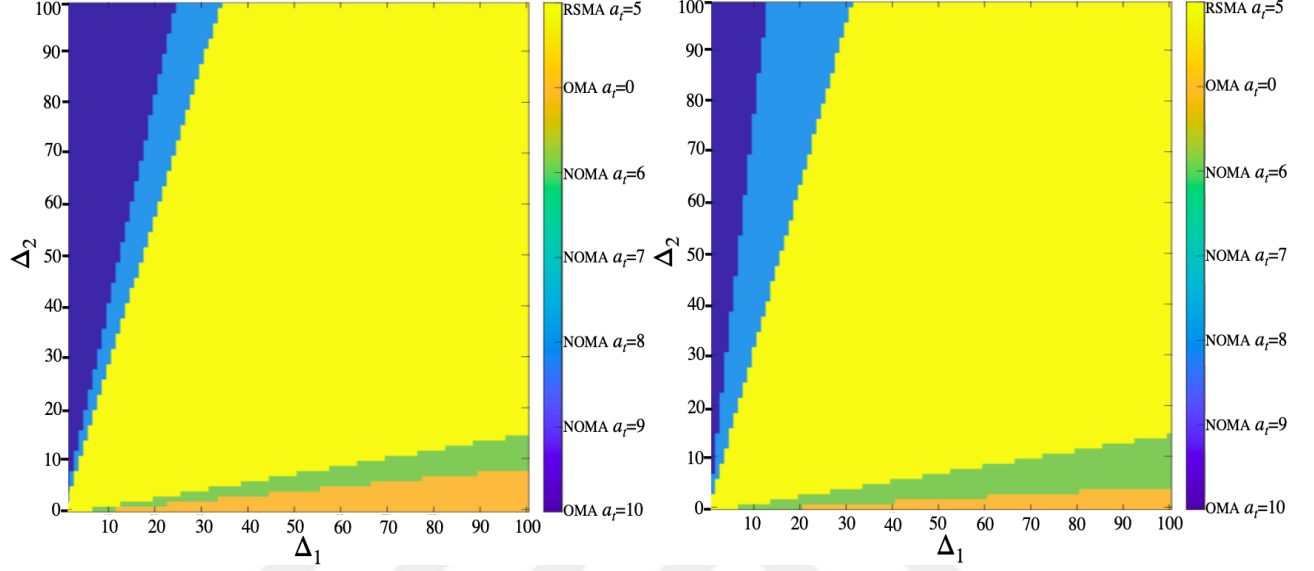


Figure C.12: Adaptive policy with unequal common target rates when $\lambda_{c,2} > \lambda_{c,1}$ [equal target rates and user weights, $\lambda_{c,1} = (0.12, 0.15), \lambda_{c,2} = (0.18, 0.20)$]



(a) $\lambda_{c,1} = 0.14, \lambda_{c,2} = 0.20, \rho = 18$ dB

(b) $\lambda_{c,1} = 0.14, \lambda_{c,2} = 0.20, \rho = 20$ dB

Figure C.13: Adaptive policy with unequal common target rates when $\lambda_{c,2} > \lambda_{c,1}$ [equal target rates and user weights, $\lambda_{c,1} = 0.14, \lambda_{c,2} = 0.20$]

Table C.3: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with unequal user weights

Policy for all actions, %					
w_1, w_2	$\lambda_{c,1}, \lambda_{c,2}$	ρ (dB)	OMA	NOMA	RSMA
(0.3, 0.7)	(0.12, 0.12)	20	8	92	0
(0.4, 0.6)	(0.12, 0.12)	20	7	93	0
(0.6, 0.4)	(0.12, 0.12)	20	12	88	0
(0.7, 0.3)	(0.12, 0.12)	20	16	84	0
(0.3, 0.7)	(0.18, 0.18)	18	14	19	67
(0.4, 0.6)	(0.18, 0.18)	18	12	11	77
(0.6, 0.4)	(0.18, 0.18)	18	16	5	79
(0.7, 0.3)	(0.18, 0.18)	18	24	3	73
(0.3, 0.7)	(0.18, 0.18)	20	7	23	70
(0.4, 0.6)	(0.18, 0.18)	20	7	14	79
(0.6, 0.4)	(0.18, 0.18)	20	10	6	84
(0.7, 0.3)	(0.18, 0.18)	20	13	4	83

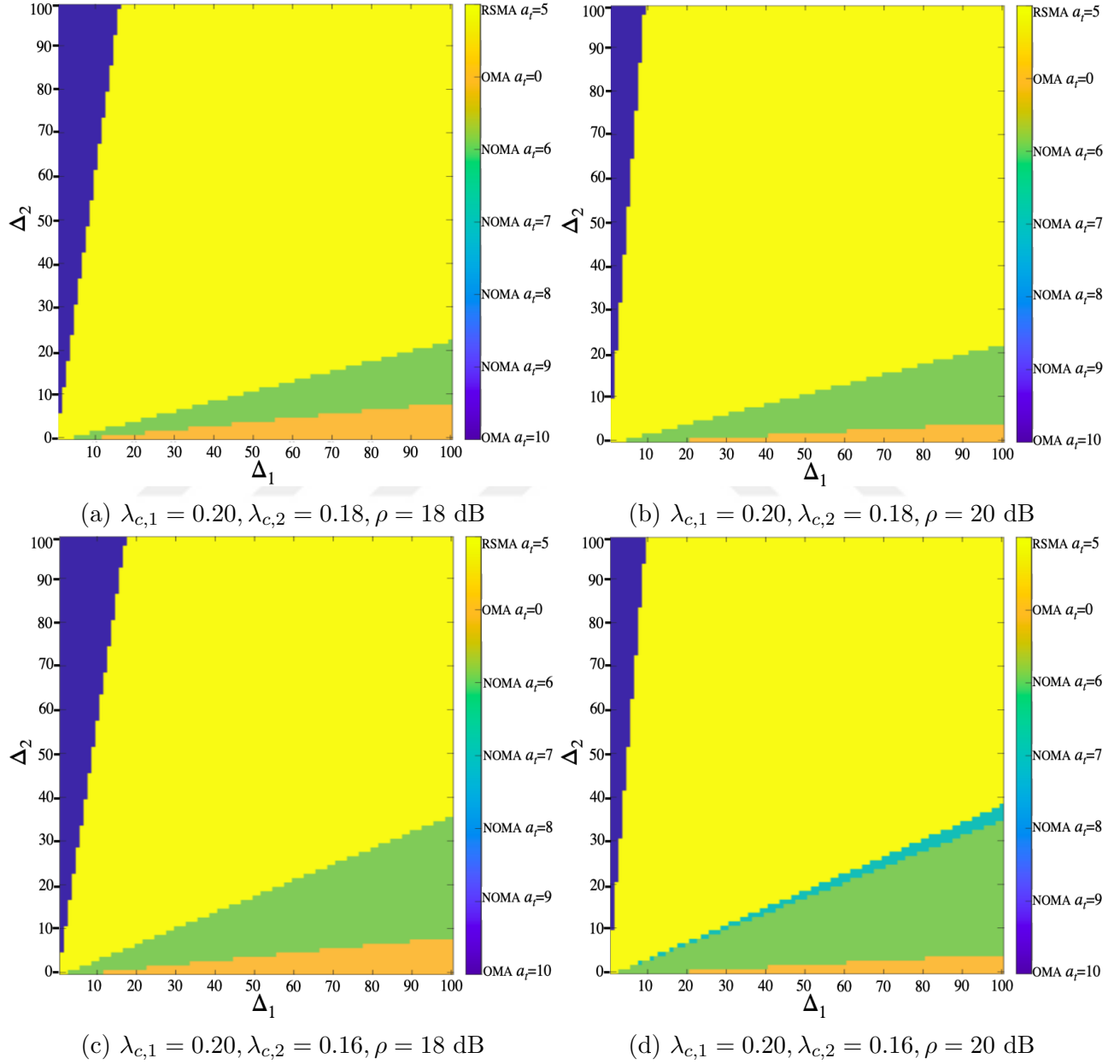


Figure C.14: Adaptive policy with unequal common target rates when $\lambda_{c,1} > \lambda_{c,2}$ [equal target rates and user weights, $\lambda_{c,1} = 0.20, \lambda_{c,2} = (0.18, 0.16)$]

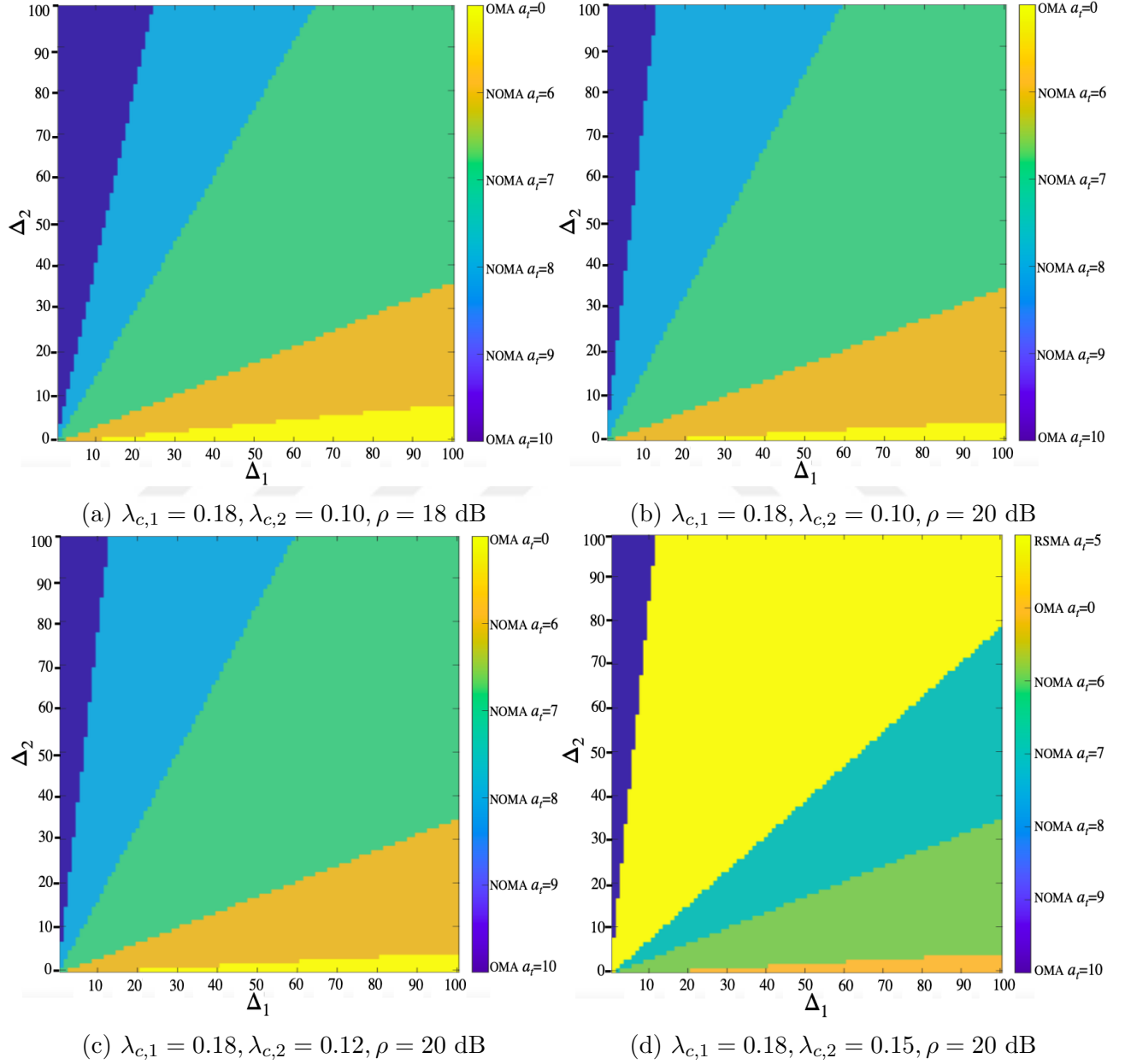


Figure C.15: Adaptive policy with unequal common target rates when $\lambda_{c,1} > \lambda_{c,2}$ [equal target rates and user weights, $\lambda_{c,1} = 0.18, \lambda_{c,2} = (0.10, 0.12, 0.15)$]

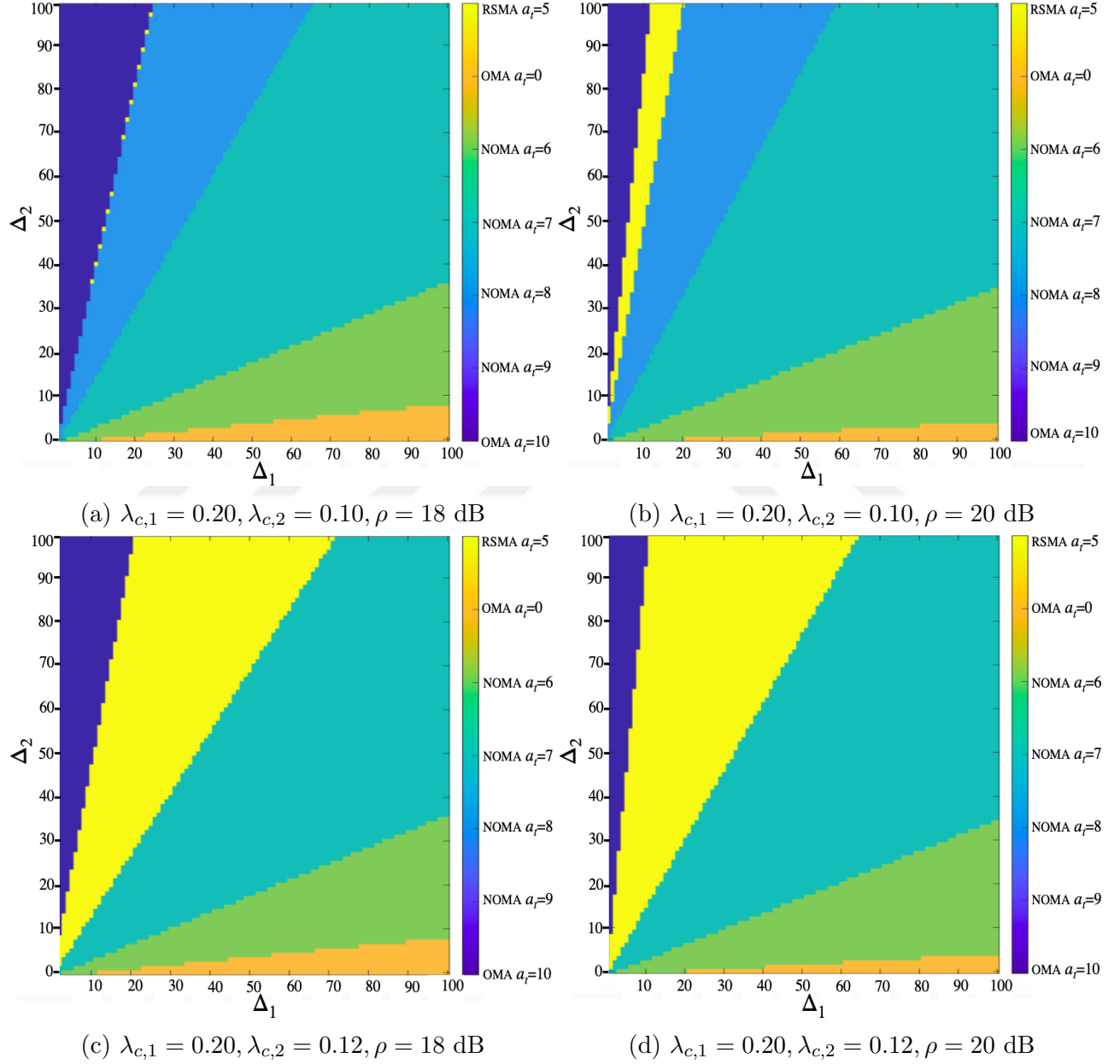


Figure C.16: Adaptive policy with unequal common target rates when $\lambda_{c,1} > \lambda_{c,2}$ [equal target rates and user weights, $\lambda_{c,1} = 0.20, \lambda_{c,2} = (0.10, 0.12)$]

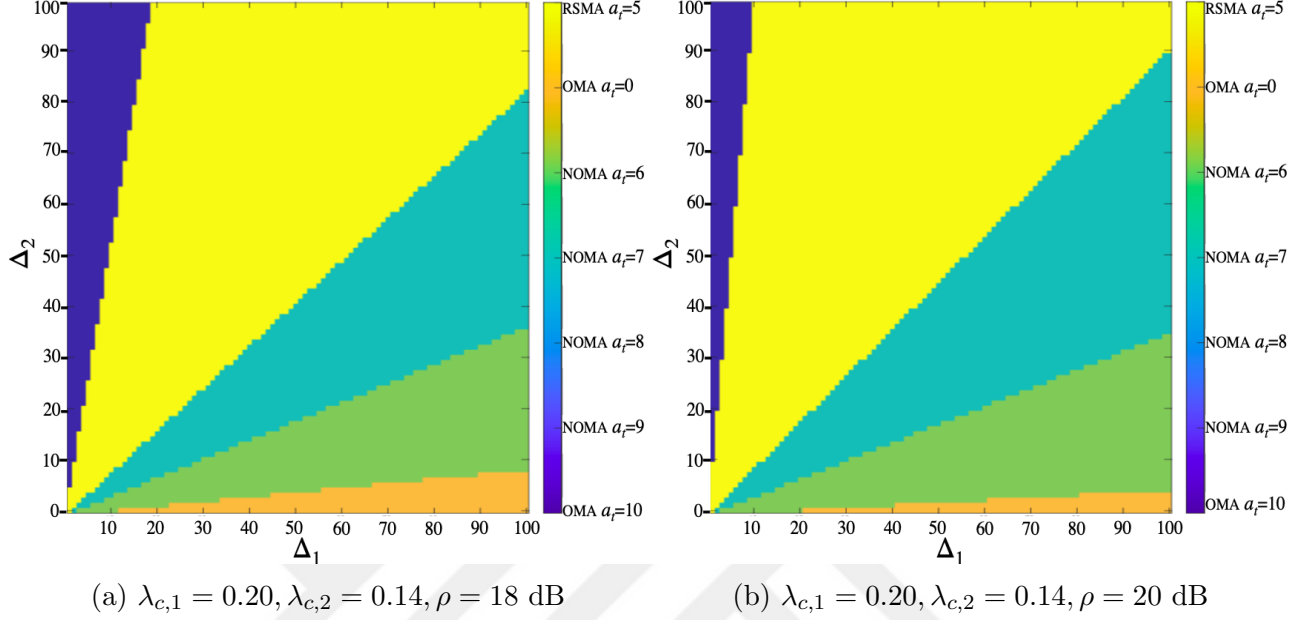


Figure C.17: Adaptive policy with unequal common target rates when $\lambda_{c,1} > \lambda_{c,2}$ [equal target rates and user weights, $\lambda_{c,1} = 0.20, \lambda_{c,2} = 0.14$]

Table C.3 shows that RSMA outperforms RSMA/NOMA/OMA above $\lambda_c > 0.12$ for the transmission SNR $\rho = 0.18$ and $\rho = 0.20$, while NOMA/OMA dominates when $\lambda_c \leq 0.12$. It is also clear that RSMA selection percentage increases with increasing the transmission SNR ρ .

C.4 Additional Adaptive Policy Graphics for Unequal Target Rates

The adaptive RSMA/NOMA/OMA policy related to the Table 5.15 and Table 5.16, where $R_1^* > R_2^*$, are given in Figure C.21 - Figure C.24 as 2-D colored graphs. Regarding the percentage of the colored areas indicating OMA, NOMA, and RSMA, above the threshold common target rate, the adaptive policy takes the actions for OMA, NOMA, and RSMA in all of the actions with the percentages shown in Table C.4. When $R_1^* > R_2^*$, $w_1 = w_2$, RSMA preference increases with increasing ρ . The rate of increase at RSMA decreases with increasing the transmission SNR ρ .

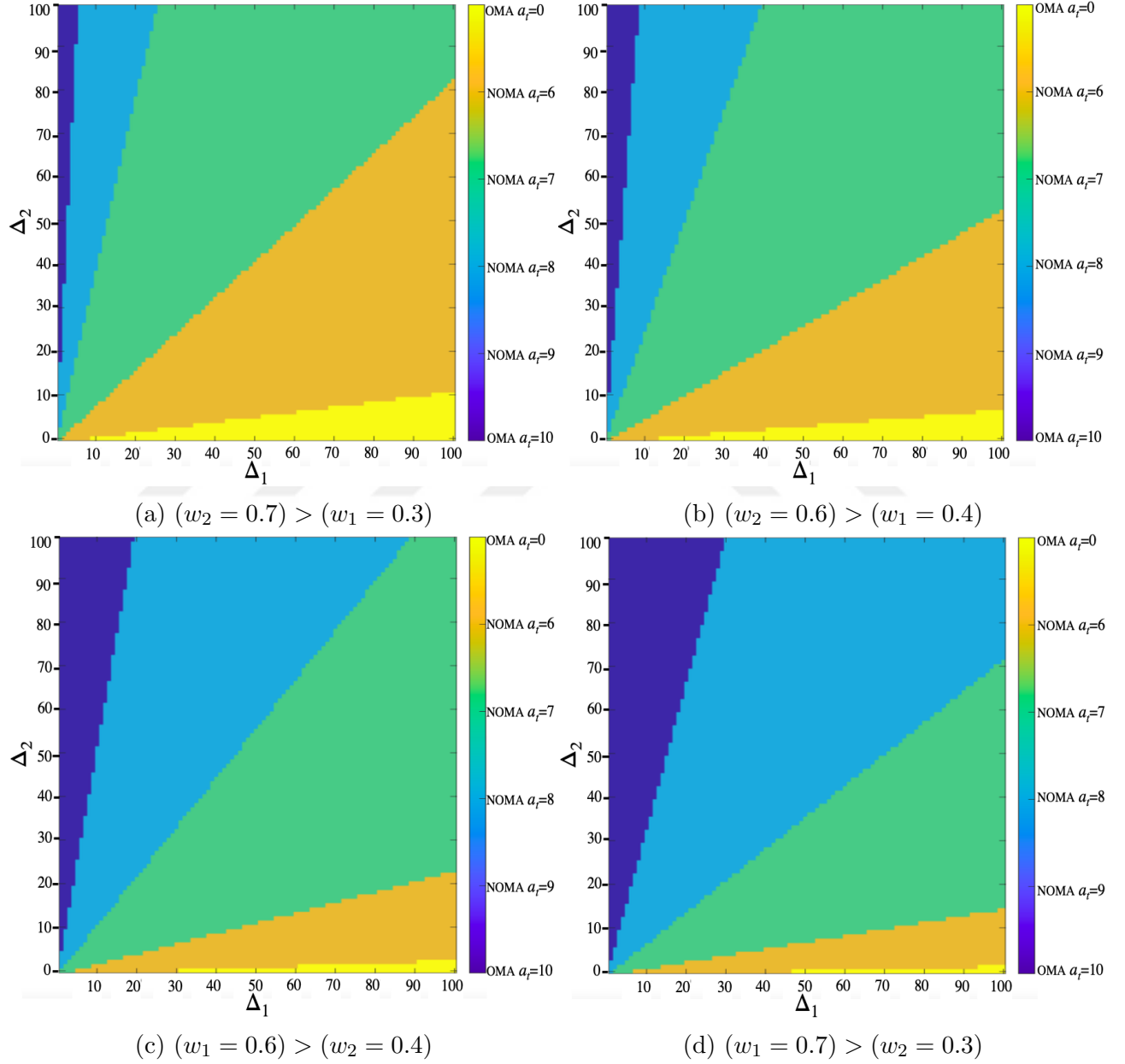


Figure C.18: Adaptive policy with unequal user weights when $\lambda_{c,1} = \lambda_{c,2} = 0.12, \rho = 20$ dB

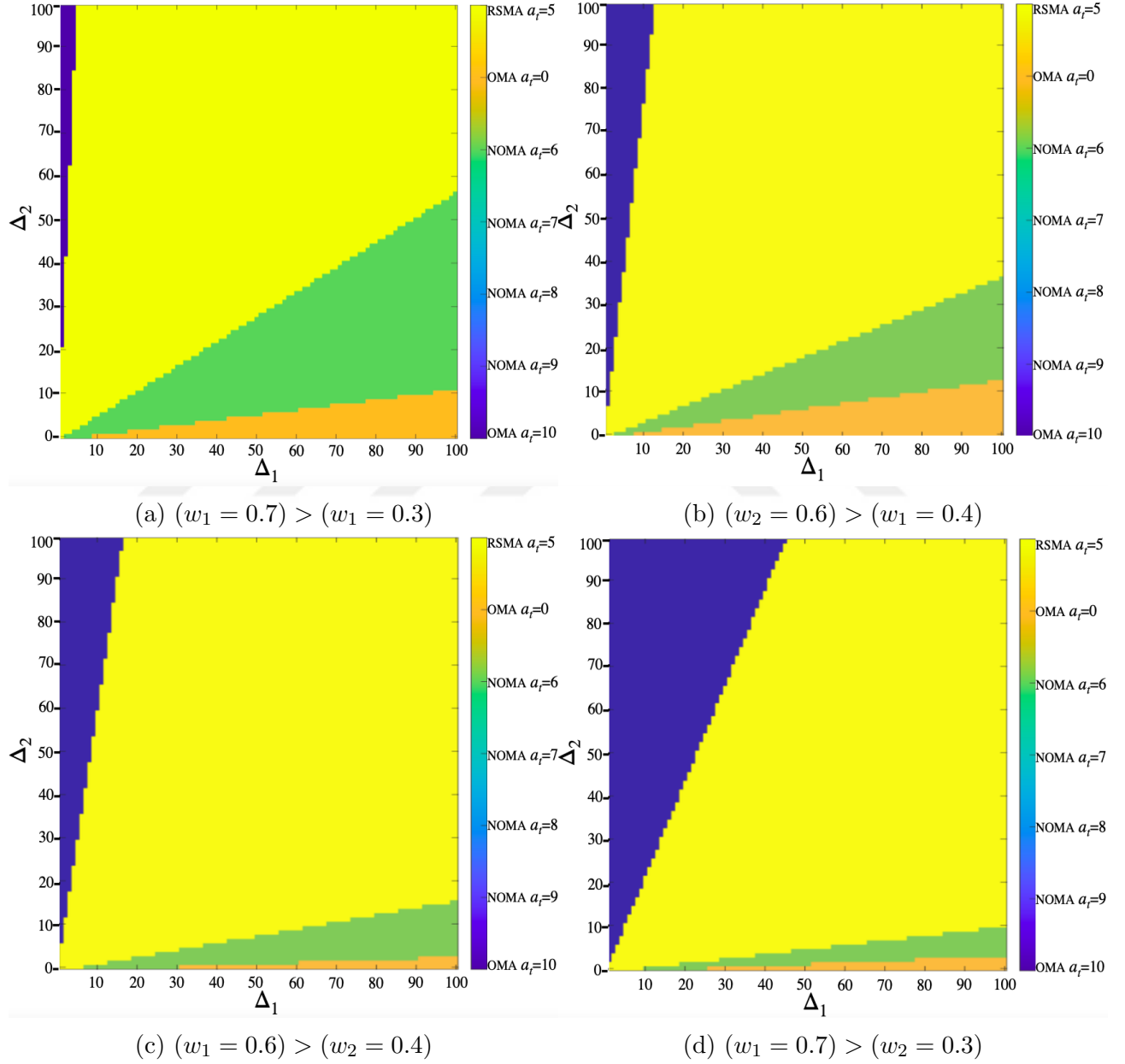


Figure C.19: Adaptive policy with unequal user weights when $\lambda_{c,1} = \lambda_{c,2} = 0.18, \rho = 18$ dB

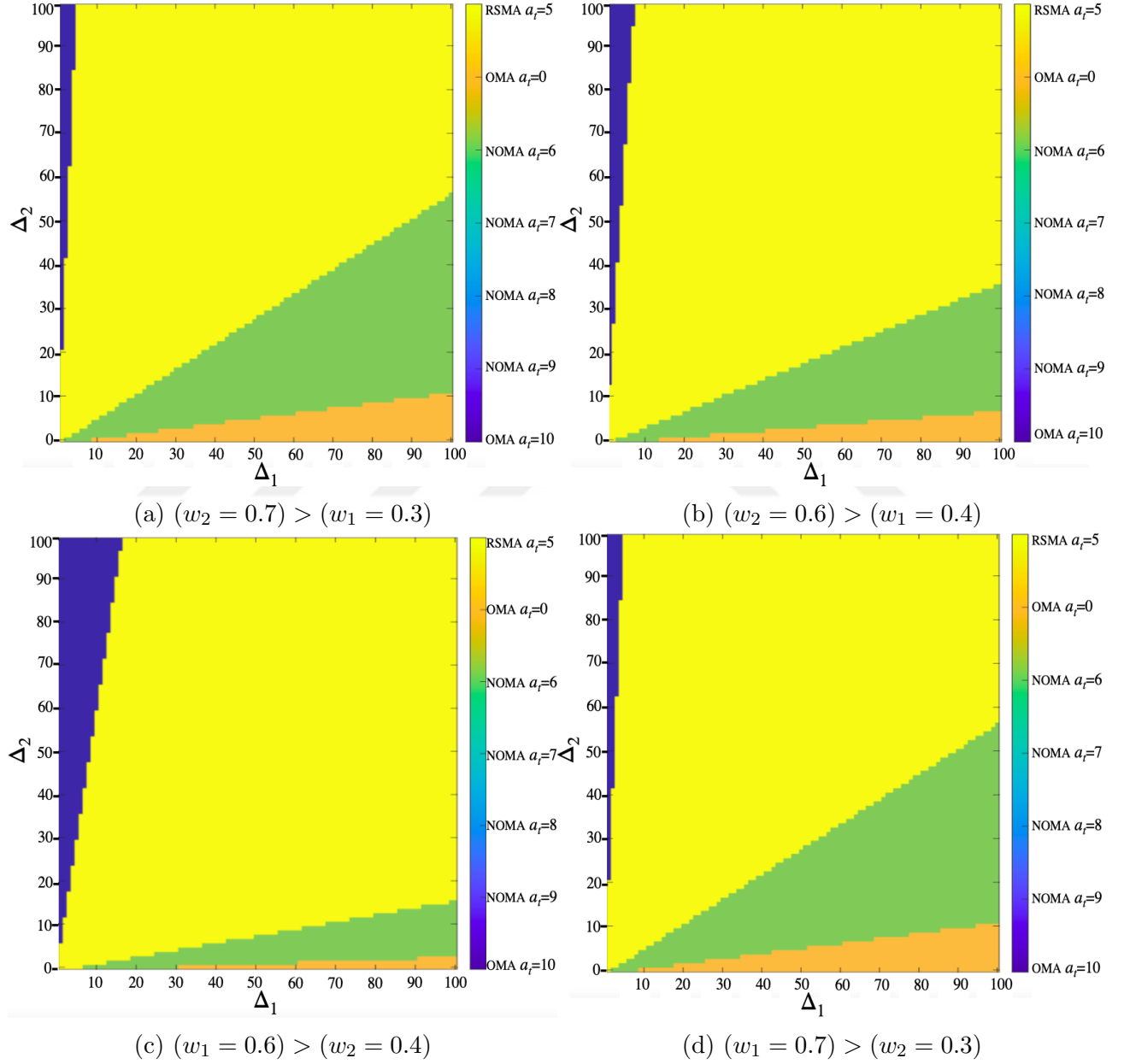


Figure C.20: Adaptive policy with unequal user weights when $\lambda_{c,1} = \lambda_{c,2} = 0.18, \rho = 20$ dB

Table C.4: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with unequal target rates when $[(R_1^* = 1.0) > (R_2^* = 0.8), (w_1 = 0.7) > (w_2 = 0.3), (R_{c,1}^* = R_{c,2}^* = 0.2)]$

ρ (dB)	Policy for all actions, %		
	OMA	NOMA	RSMA
12	17	0	83
13	14	0	86
13.5	11	0	89
14	9	0	91
15	6	0	94
15.5	5	0	95
17	3	0	97
17.5	2	0	98
18	2	0	98
18.5	2	0	98
19	1	0	99
19.5	1	0	99
20	1	0	99

The adaptive RSMA/NOMA/OMA policy related to the Table 5.17 and Table 5.18, where $R_2^* > R_1^*$ and $w_2 > w_1$ are shown in Figure C.25 - Figure C.26 as 2-D colored graphs. Regarding the percentage of the colored areas indicating OMA, NOMA, and RSMA, above the threshold common target rate, the adaptive policy takes the actions for OMA, NOMA, and RSMA in all of the actions with the percentages shown in Table C.5. When $R_2^* > R_1^*$, $w_2 > w_1$, RSMA preference increases with increasing ρ . The rate of increase at RSMA decreases with increasing the transmission SNR ρ .

Table C.5: Adaptive policy for RSMA/NOMA/OMA in percentages for the scenarios with unequal target rates when $[(R_2^* = 1.0) > (R_1^* = 0.8), (w_2 = 0.7) > (w_1 = 0.3), (R_{c,1}^* = R_{c,2}^* = 0.2)]$

Policy for all actions, %			
ρ (dB)	OMA	NOMA	RSMA
13	5.0	0	95.0
14	3.5	0	96.5
15	2.5	0	97.5
16	1.0	0	99.0
17	0.4	0	99.6
18	0.3	0	99.7
19	0.2	0	99.8
20	0.1	0	99.9

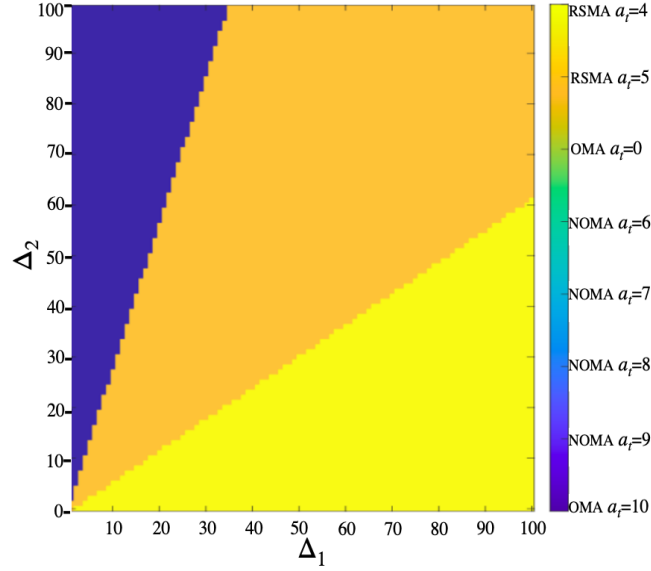


Figure C.21: Adaptive policy with $[(R_1^* = 1.0) > (R_2^* = 0.8), (w_1 = 0.7) > (w_2 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2, \rho = 12$ dB

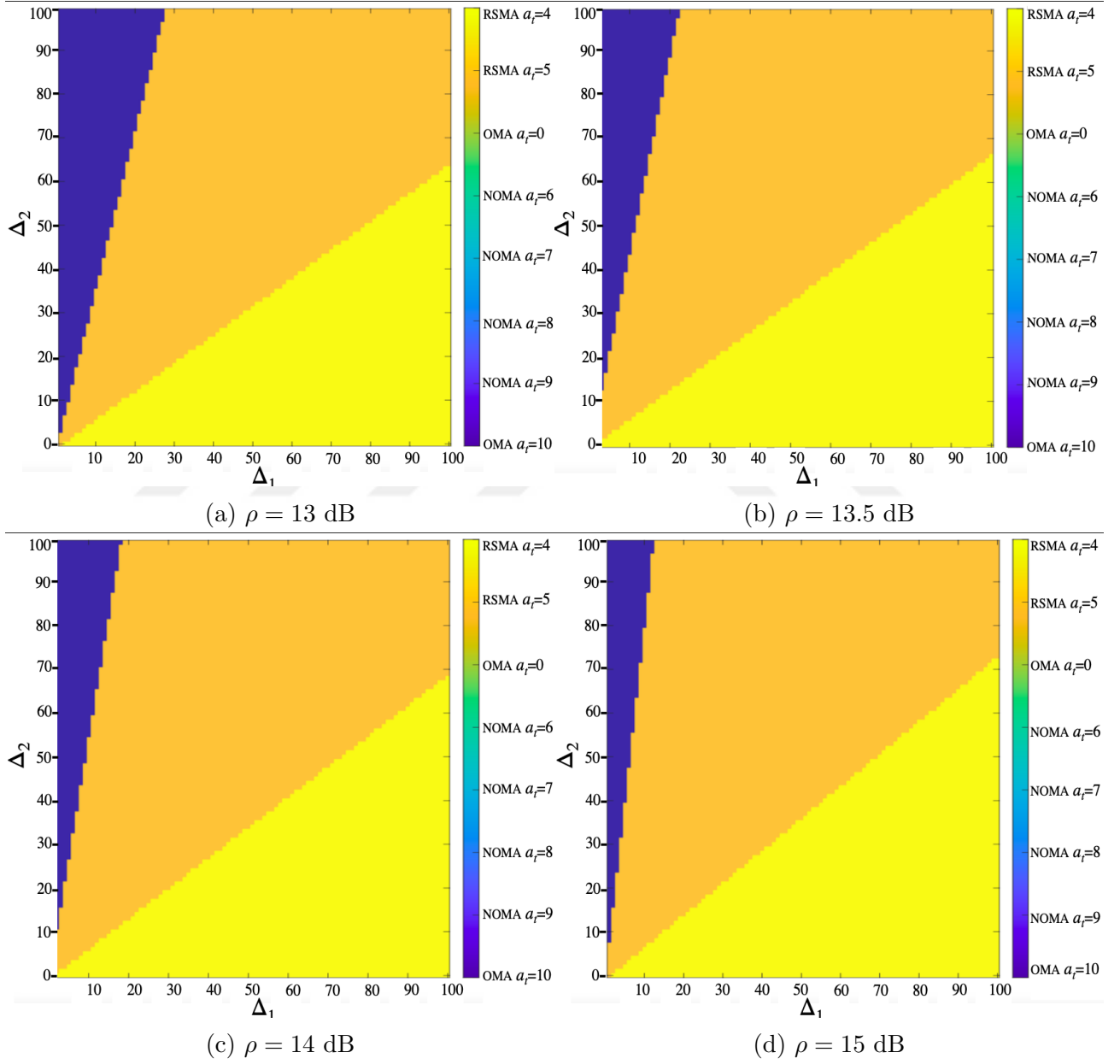


Figure C.22: Adaptive policy with $[(R_1^* = 1.0) > (R_2^* = 0.8), (w_2 = 1.0) > (w_1 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2$ [$\rho = 13 - 15$ dB]

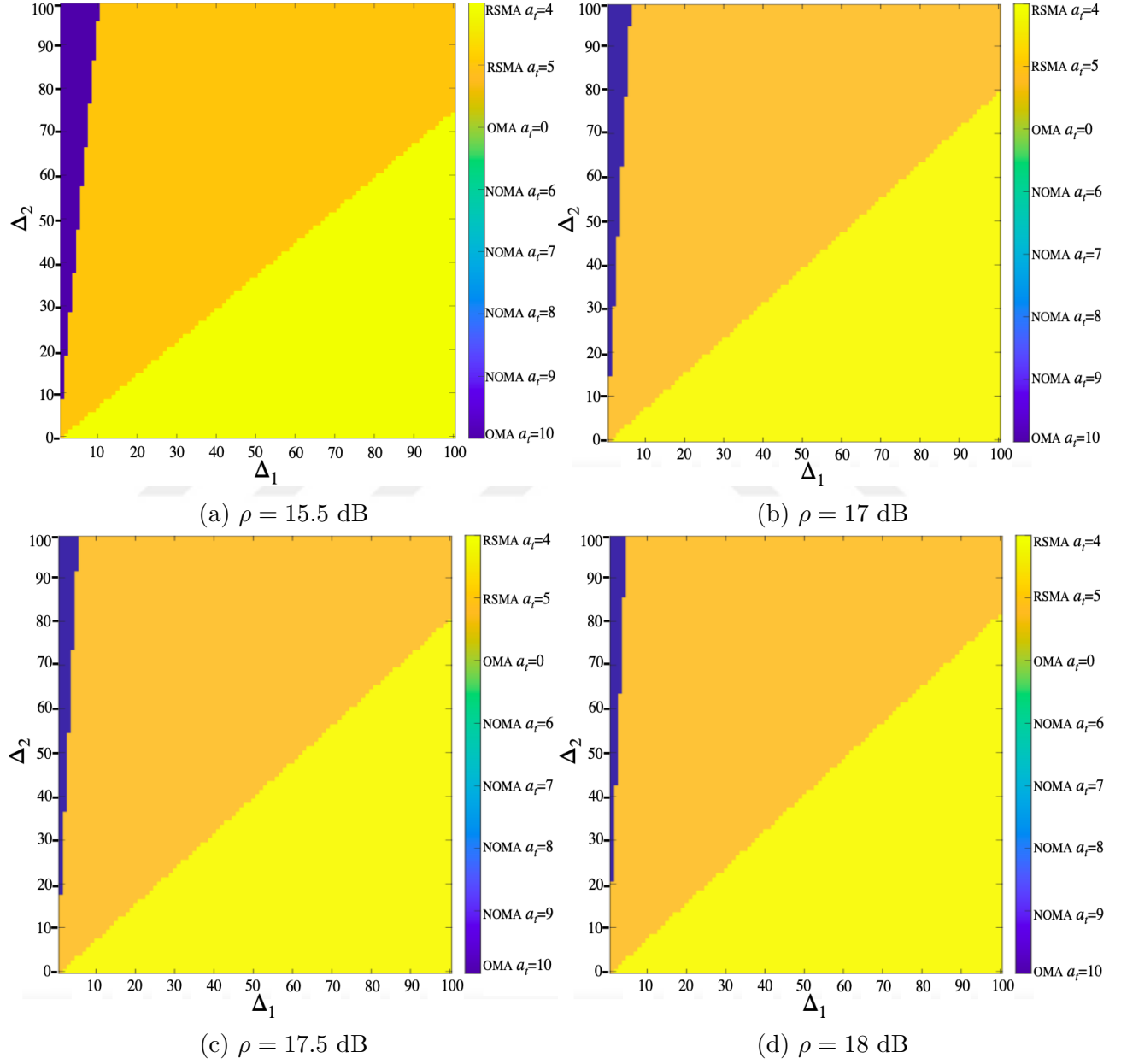


Figure C.23: Adaptive policy with $[(R_1^* = 1.0) > (R_2^* = 0.8), (w_2 = 1.0 > (w_1 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2$ [$\rho = 15.5 - 18$ dB]

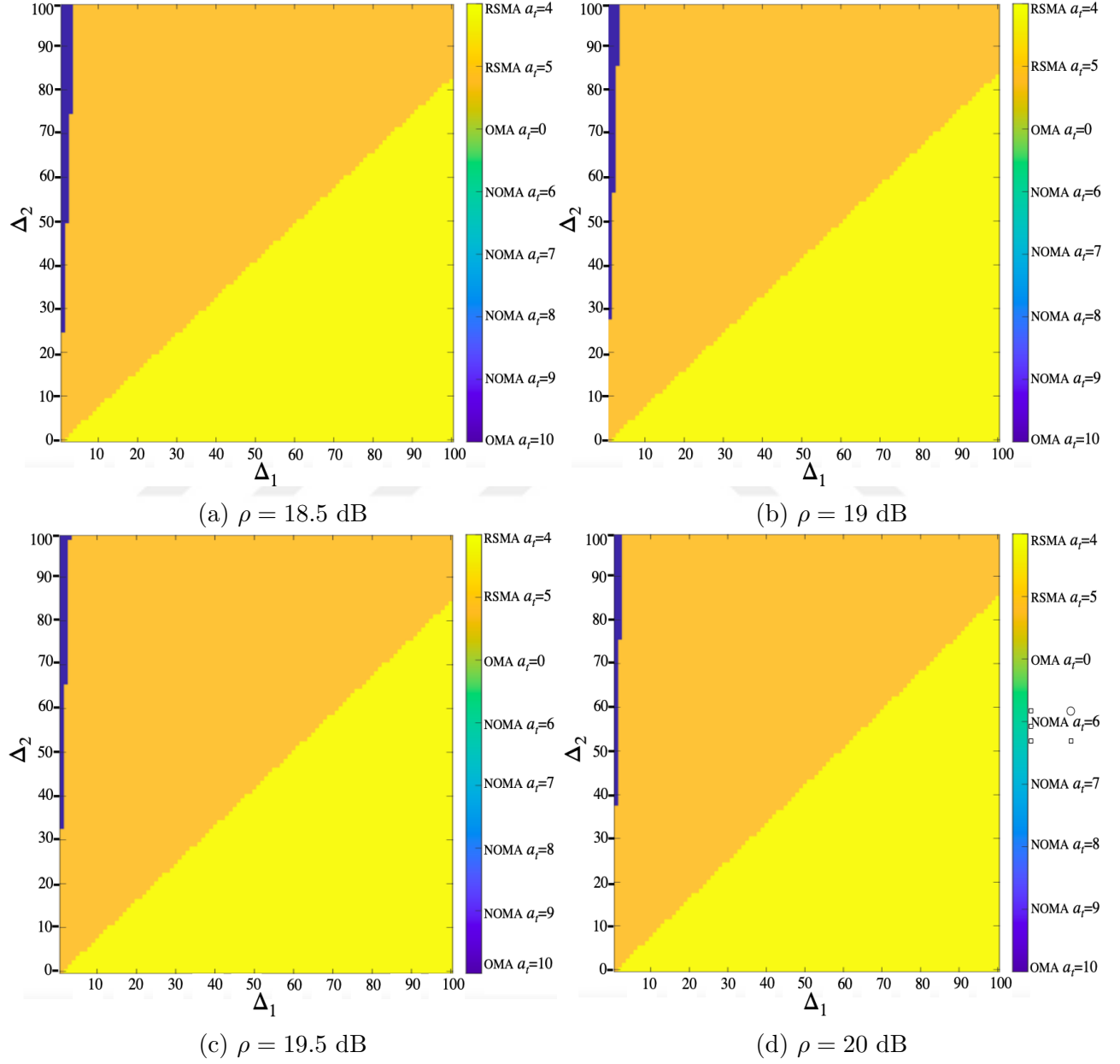


Figure C.24: Adaptive policy with $[(R_1^* = 1.0) > (R_2^* = 0.8), (w_1 = 0.7) > (w_2 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2$ [$\rho = 18.5 - 20$ dB]

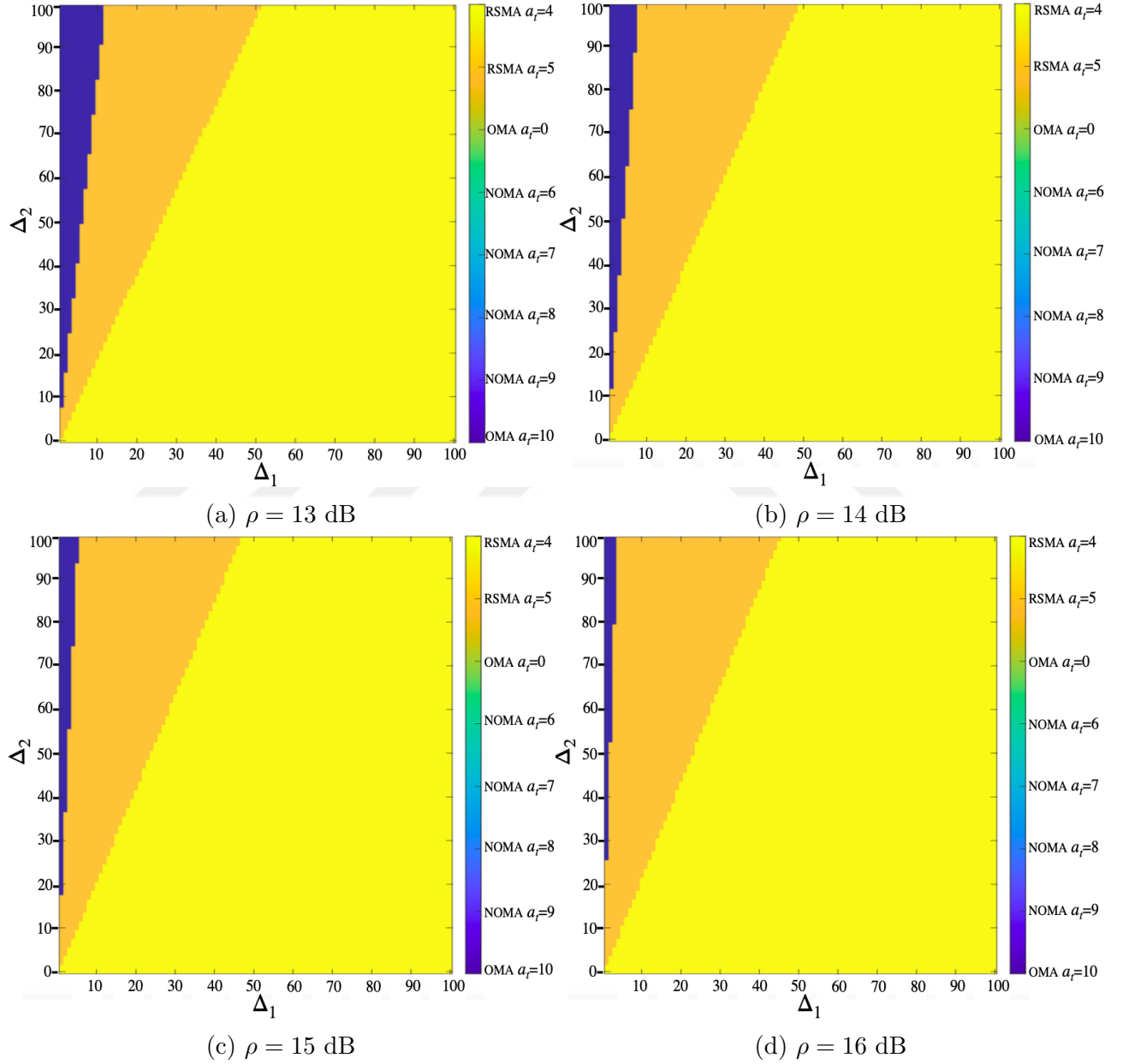


Figure C.25: Adaptive policy with $[(R_2^* = 1.0) > (R_1^* = 0.8), (w_2 = 0.7) > (w_1 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2$ [$\rho = 13 - 16$ dB]

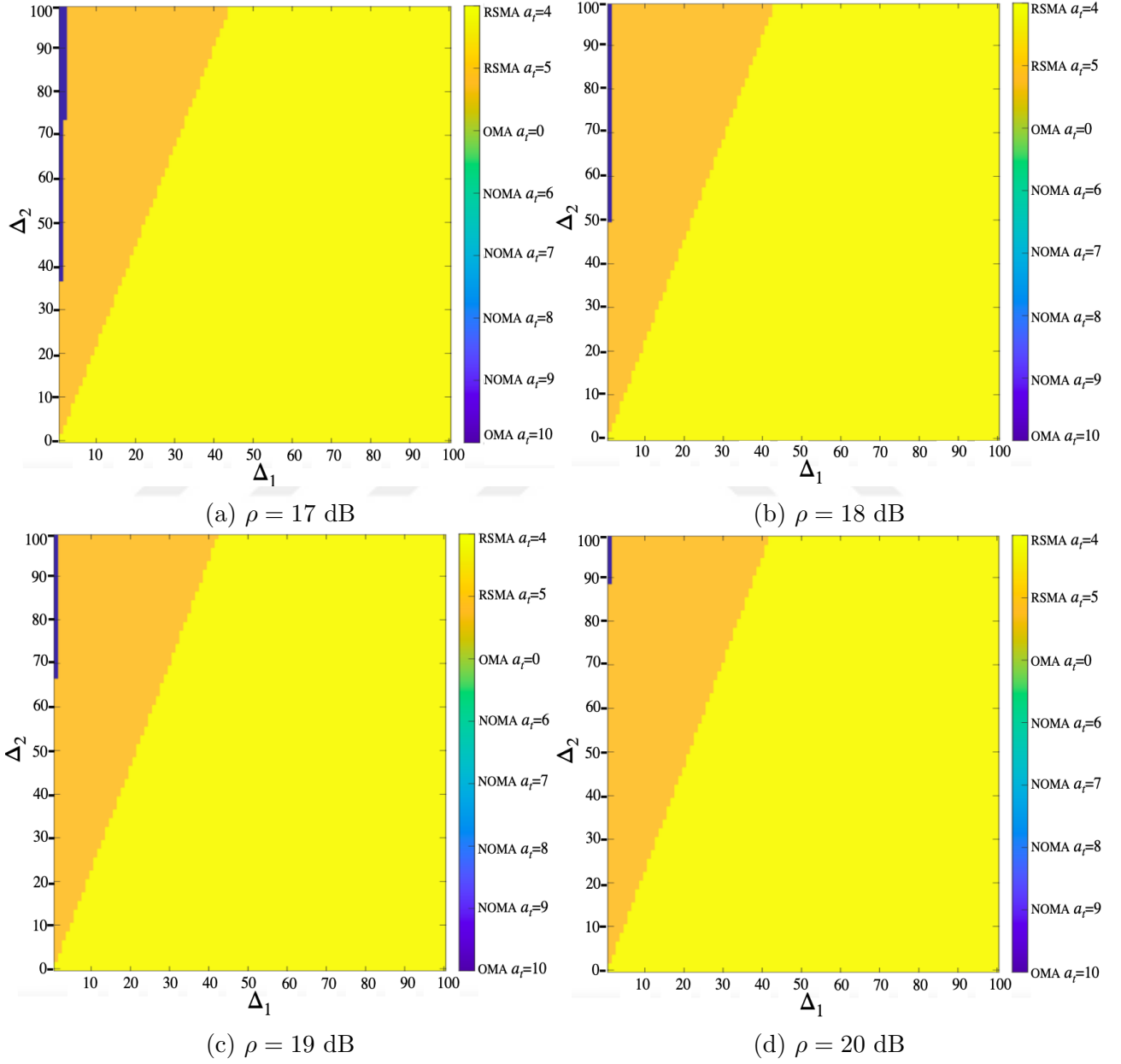


Figure C.26: Adaptive policy with $[(R_2^* = 1.0) > (R_1^* = 0.8), (w_2 = 0.7) > (w_1 = 0.3)]$ when $R_{c,1}^* = R_{c,2}^* = 0.2$ [$\rho = 17 - 20$ dB]

Appendix D

Additional Age-Energy Tradeoff Graphics

D.1 Additional Age-Energy Tradeoff Graphics for Equal Target Rates with Equal Common Target Rates, and Equal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under equal target rates and equal user weights with equal common target rates is investigated for different values for distances of users from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under equal user weight distribution are given in the Table D.1, Figure D.1 and Figure D.2. These results are the ones that are additional to the example cases given in Chapter 5.

Figure D.1 and Figure D.2 show that increasing user distances to BS increases

Table D.1: Simulation parameters for age-energy tradeoff for equal target rates with equal common rates, and equal user weights

Parameter	Value
$R_1^* = R_2^*$	1.0
$\lambda_{c,1} = \lambda_{c,2}$	0.19, 0.18, 0.17, 0.16, 0.15, 0.14
$w_1 = w_2$	0.5
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (3,6)

WSAoI substantially, especially at low values of SNR. This observation is shown graphically in Figure D.3(a) for SNR=15 dB. Effect of user distance on WSAoI decreases with increasing λ_c .

Figure D.3(b) shows SNR- λ_c relationship for a selected value of WSAoI. This figure shows effect of user distance and λ_c on SNR in case WSAoI is to be constant, e.g. 5. SNR decreases with decreasing user distance and increasing λ_c .

RSMA selection provides the better age-energy tradeoff values for all cases than for RSMA/NOMA/OMA and NOMA/OMA selections. The only exception is for $\lambda_{c,1} = \lambda_{c,2} = 0.14$ at which RSMA/NOMA/OMA scheme provides the results better than RSMA. This exception is observed when λ_c is below the threshold value.

D.2 Additional Age-Energy Tradeoff Graphics for Equal Target Rates with Unequal Common Rates, and Equal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under equal target rates and equal user weights with unequal common target rates is investigated for different values for distances of users

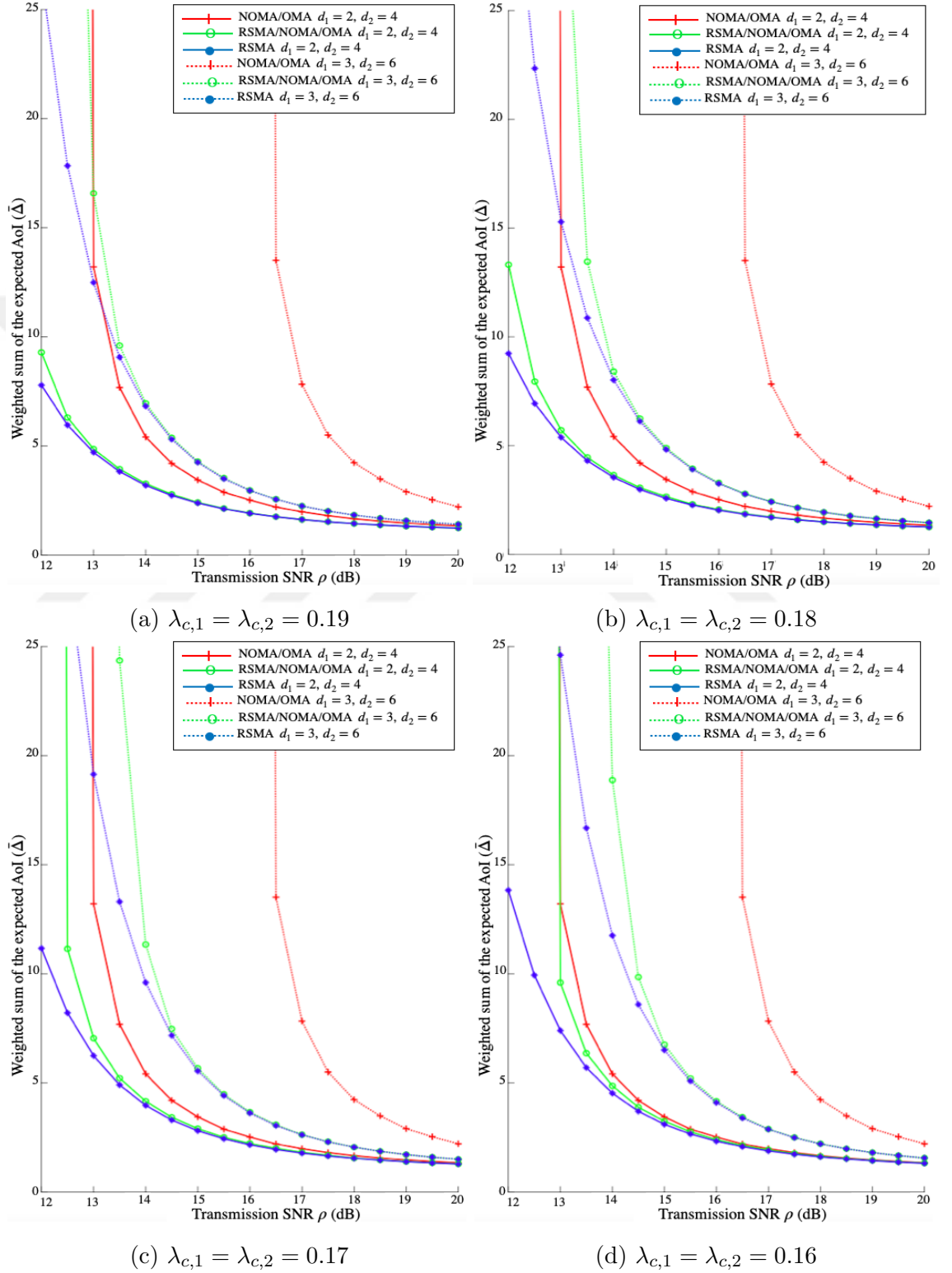


Figure D.1: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = R_2^* = 1.0), (\lambda_{c,1} = \lambda_{c,2} = 0.19 - 0.16), (w_1 = w_2 = 0.5)]$

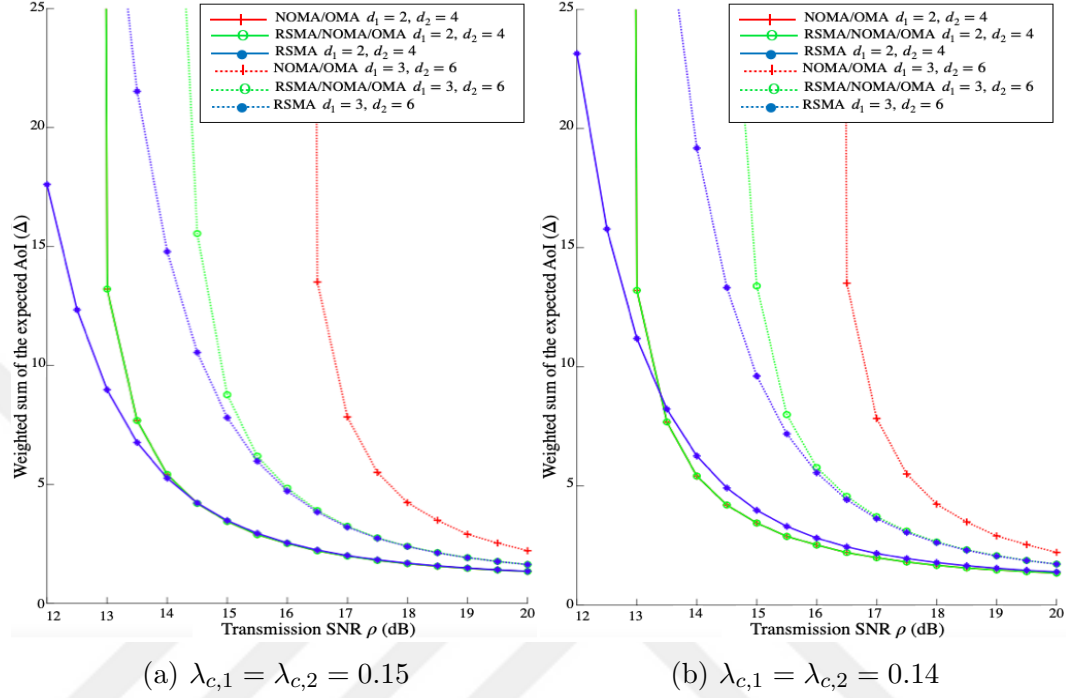
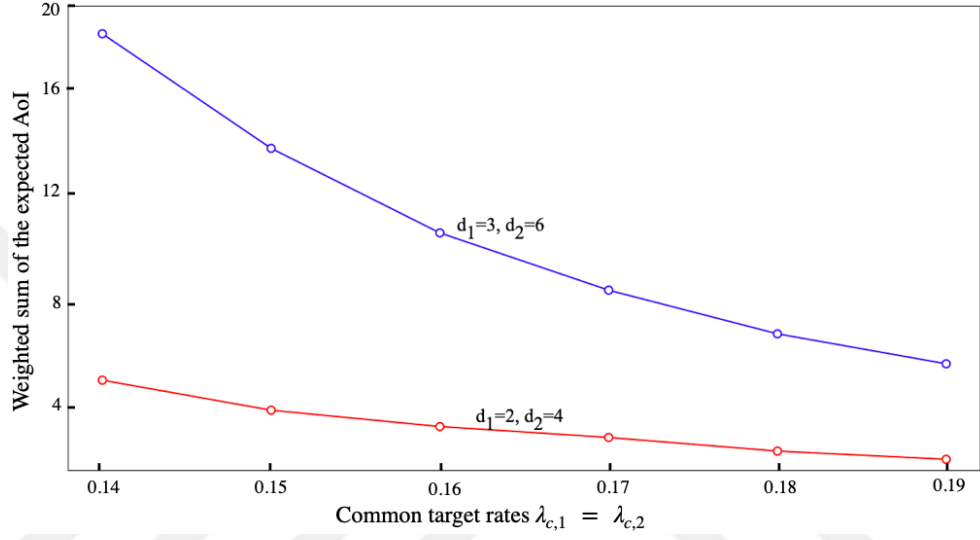


Figure D.2: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = R_2^* = 1.0), (\lambda_{c,1} = \lambda_{c,2} = 0.15, 0.14), (w_1 = w_2 = 0.5)]$

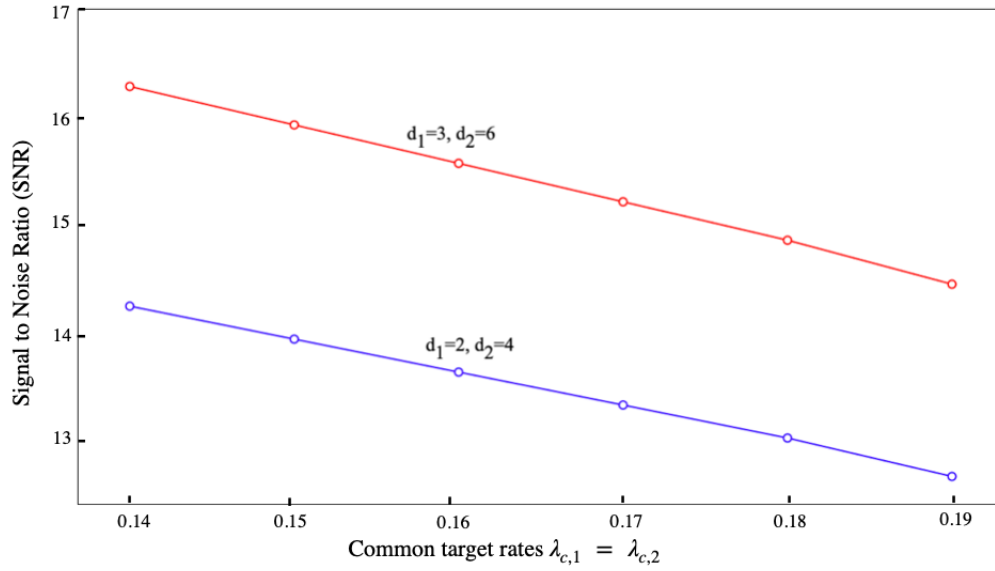
from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under equal user weight distribution are given in the Table D.2, Figure D.4 and Figure D.5. These are graphics that are additional to the ones given in Chapter 5. Figure D.4 shows effect of user distance and SNR on WSAoI when $\lambda_{c,1}$ is kept constant and $\lambda_{c,2}$ is decreased. For all cases, increasing user distance or decreasing SNR increases WSAoI. Decreasing far user's λ_c while keeping the near user's λ_c constant.

Figure D.5 shows effect of user distance and SNR on WSAoI when $\lambda_{c,2}$ is kept constant and $\lambda_{c,1}$ is decreased. For all cases, increasing user distance or decreasing SNR increases WSAoI. Decreasing near user's λ_c while keeping the far user's λ_c constant.

Comparing Figure D.4 with Figure D.5 shows that reducing the near user's λ_c while keeping far user's λ_c constant is more effective on reducing WSAoI than reducing far user's λ_c while keeping near user's λ_c constant.

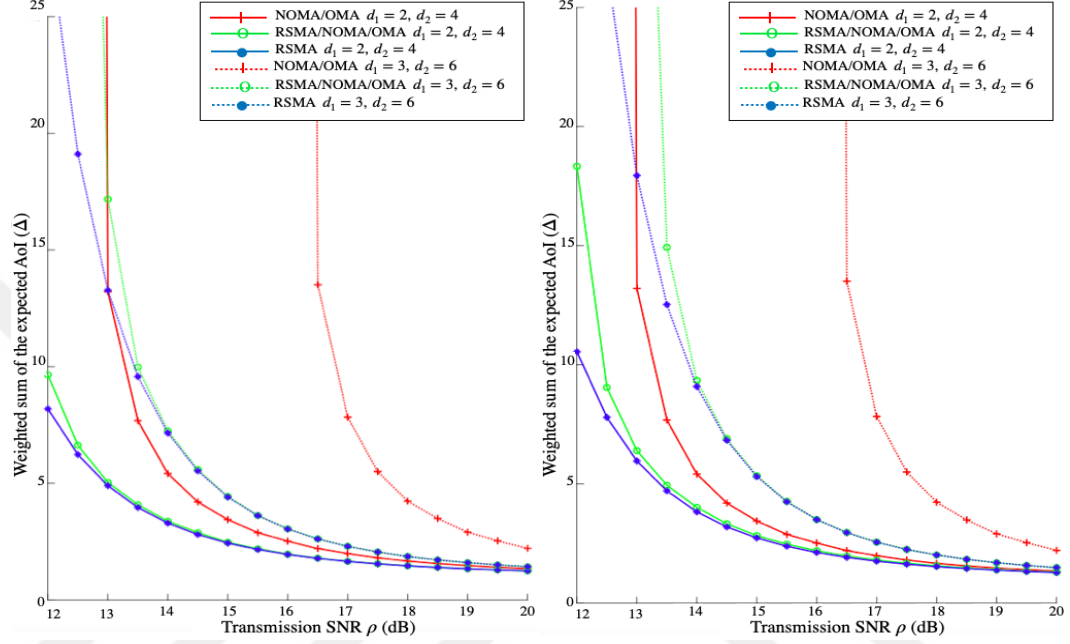


(a) Values with RSMA values at SNR=15 dB



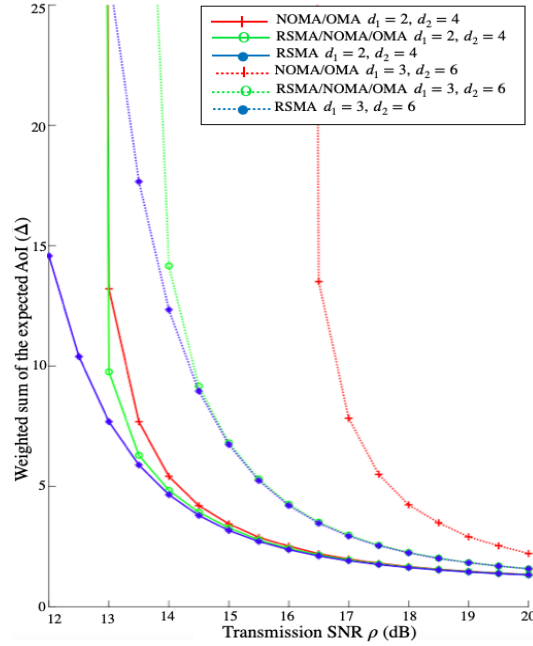
(b) Values for WSAoI=5

Figure D.3: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = R_2^* = 1.0), (\lambda_{c,1} = \lambda_{c,2}), (w_1 = w_2 = 0.5)]$



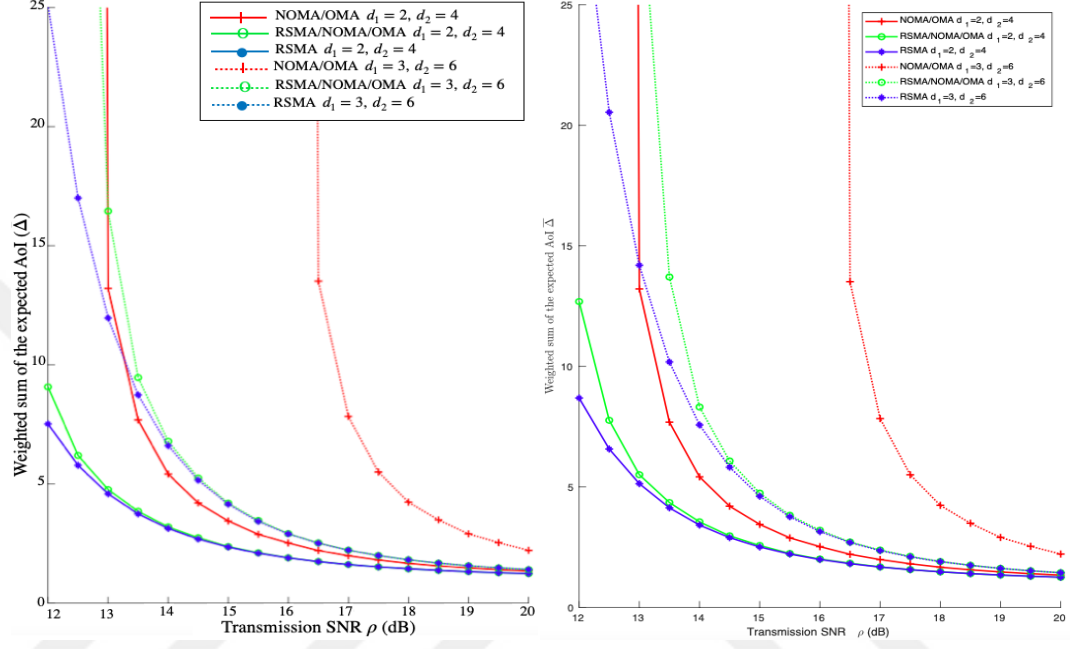
(a) $(\lambda_{c,1} = 0.20) > (\lambda_{c,2} = 0.18)$

(b) $(\lambda_{c,1} = 0.20) > (\lambda_{c,2} = 0.16)$



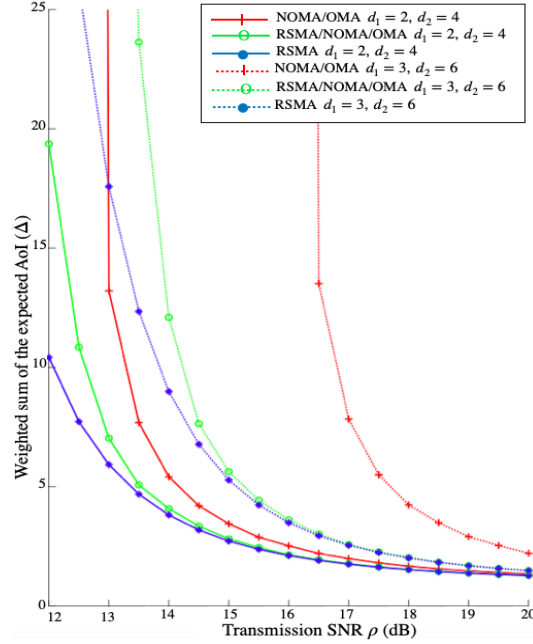
(c) $(\lambda_{c,1} = 0.20) > (\lambda_{c,2} = 0.14)$

Figure D.4: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$ $[(R_1^* = R_2^* = 1.0), (\lambda_{c,1} = 0.20) > (\lambda_{c,2} = 0.18 - 0.14), (w_1 = w_2 = 0.5)]$



(a) $(\lambda_{c,2} = 0.20) > (\lambda_{c,1} = 0.18)$

(b) $(\lambda_{c,2} = 0.20) > (\lambda_{c,1} = 0.16)$



(c) $(\lambda_{c,2} = 0.20) > (\lambda_{c,1} = 0.14)$

Figure D.5: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$ $[(R_1^* = R_2^* = 1.0), (\lambda_{c,2} = 0.20) > (\lambda_{c,1} = 0.18 - 0.14), (w_1 = w_2 = 0.5)]$

Table D.2: Simulation parameters for age-energy tradeoff for equal target rates with equal common rates, and equal user weights

Parameter	Value
$R_1^* = R_2^*$	1.0
$\lambda_{c,1} = \lambda_{c,2}$	0.19, 0.18, 0.17, 0.16, 0.15, 0.14
$w_1 = w_2$	0.5
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (3,6)

D.3 Additional Age-Energy Tradeoff Graphics for Equal Common Unequal Private Target Rates, and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under unequal target rates and unequal user weights with equal common target rates while changing private target rates is investigated for different values for distances of users from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are given in the Table D.3, and in Figure D.6 for $R_1^* > R_2^*$, $[(w_1 > w_2), (w_2 > w_1)]$ and in Figure D.7 for $R_2^* > R_1^*$, $[(w_1 > w_2), (w_2 > w_1)]$ for the scenarios with $R_{c,1} = R_{c,2} = 0.15$.

Figure D.6 and Figure D.7 indicate that RSMA scheme outperforms NOMA/OMA schemes for both $R_1^* > R_2^*$ ($R_{p,1}^* > R_{p,2}^*$) and $R_2^* > R_1^*$ ($R_{p,2}^* > R_{p,1}^*$), for both user distances $\{(d_1 = 2, d_2 = 4), (d_1 = 3, d_2 = 6)\}$, and at all ranges of SNR (ρ) (0.12 - 0.20). It is also observed that both RSMA and RSMA/NOMA/OMA schemes take the same actions, and the related curves coincide.

Table D.3: Simulation parameters for age-energy tradeoff under equal common, unequal private target rates and unequal user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$R_{c,1} = R_{c,2}$	0.15
$R_{p,1} \neq R_{p,2}$	(0.85,0.65),(0.65,0.85)
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (3,6)

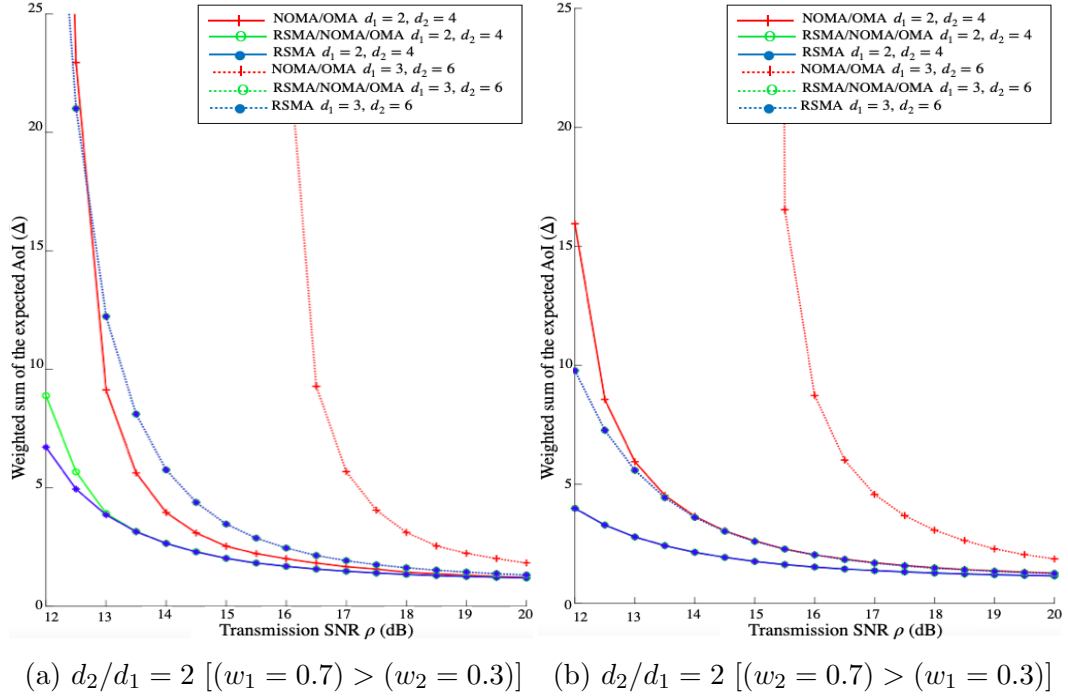


Figure D.6: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = 1.0) > (R_2^* = 0.8), (R_{c,1} = R_{c,2} = 0.15)]$

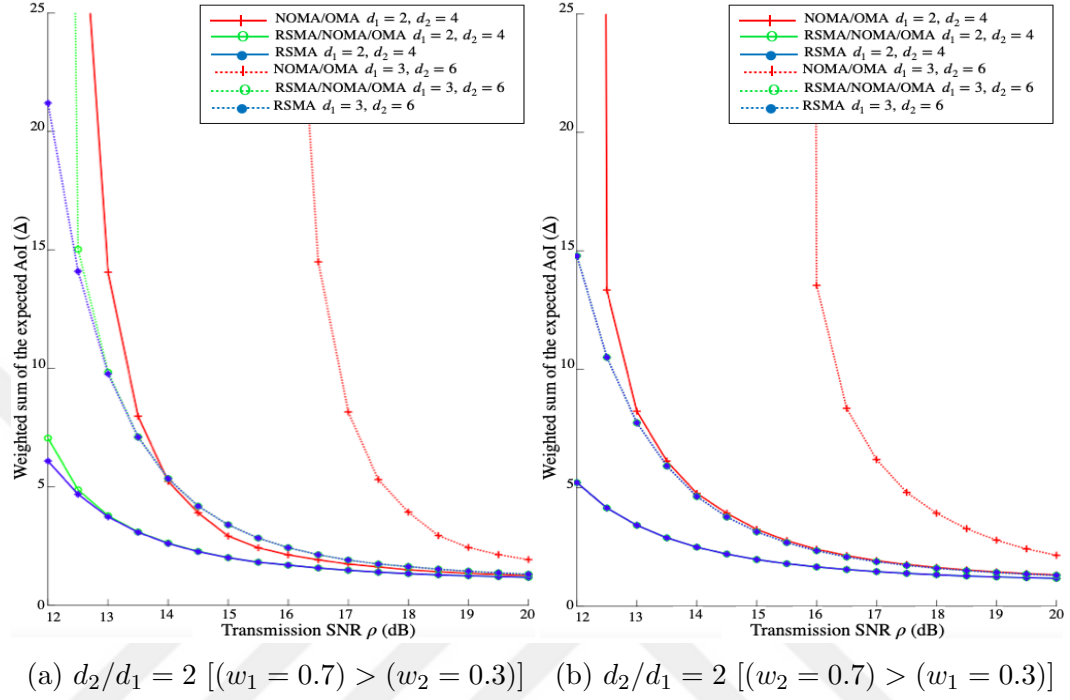


Figure D.7: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_2^* = 1.0) > (R_1^* = 0.8), (R_{c,1}^* = R_{c,2}^* = 0.15)]$

Comparing Figure D.6 with Figure D.12 show that, without changing the user weights and target rates, while keeping the user 2's common target rate constant, increasing user 1's common target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher.

Similarly, comparing Figure D.7 with Figure D.13 show that, without changing the user weights and target rates, while keeping the user 1's common target rate constant, increasing user 2's common target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher. Considering this observation and the observation given in the previous paragraph, it can be concluded that, without changing the user weights and target rates, while keeping one user's common target rate constant, increasing the other user's common target rate decreases WSAoI substantially.

Age-energy tradeoff study for change of private target rate of one user while

keeping the common target rates of both users and private target rate of the other user constant can also be shown by comparing Figure 5.18(a) with Figure D.6(a) and Figure D.7(a) for $w_1 > w_2$, and Figure 5.19(a) with Figure D.6(b) and Figure D.7(b) for $w_1 < w_2$. For convenience of showing different figures together, these comparisons are re-given in Figure D.8, Figure D.9, Figure D.10 and Figure D.11.

Comparisons of Figure D.8, Figure D.9, Figure D.10, and Figure D.11 show that, decreasing one user's private target rate, while keeping both users' common target rates, user weights and the other user's private rate constant, decreases WSAoI substantially for $w_1 > w_2$, $w_2 > w_1$ cases. Reduction in WSAoI is the highest if the far user's private rate is decreased when far user's weight is higher, and the smallest if its weight is less than the rear user's weight. The reduction due to decrease of rear user's private rate, when its weight is less, is larger than the case when its weight is less than the far user's weight.

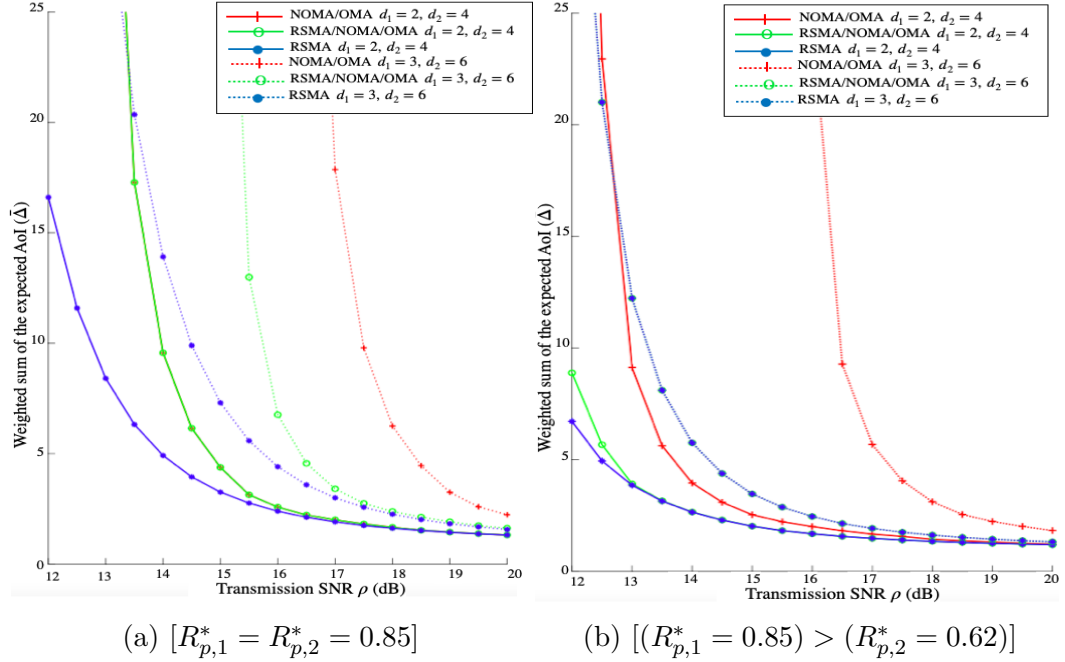


Figure D.8: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.7) > (w_2 = 0.3)]$, equal common target rates, far user's private target rate changing]

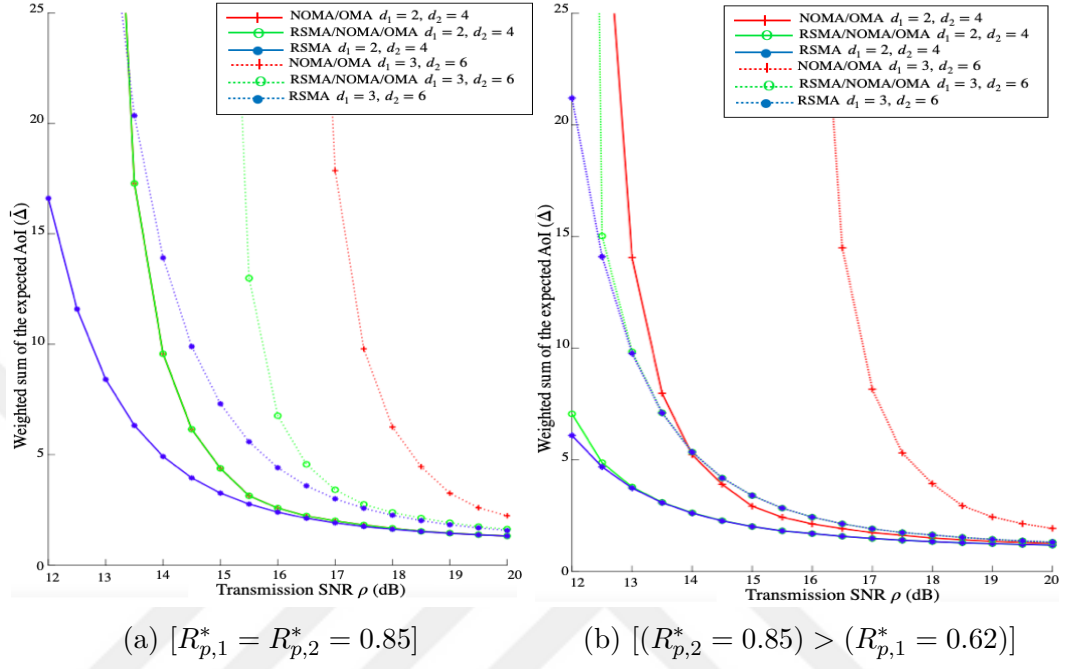


Figure D.9: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_1 = 0.7) > (w_2 = 0.3)]$, equal common target rates, far user's private target rate changing]

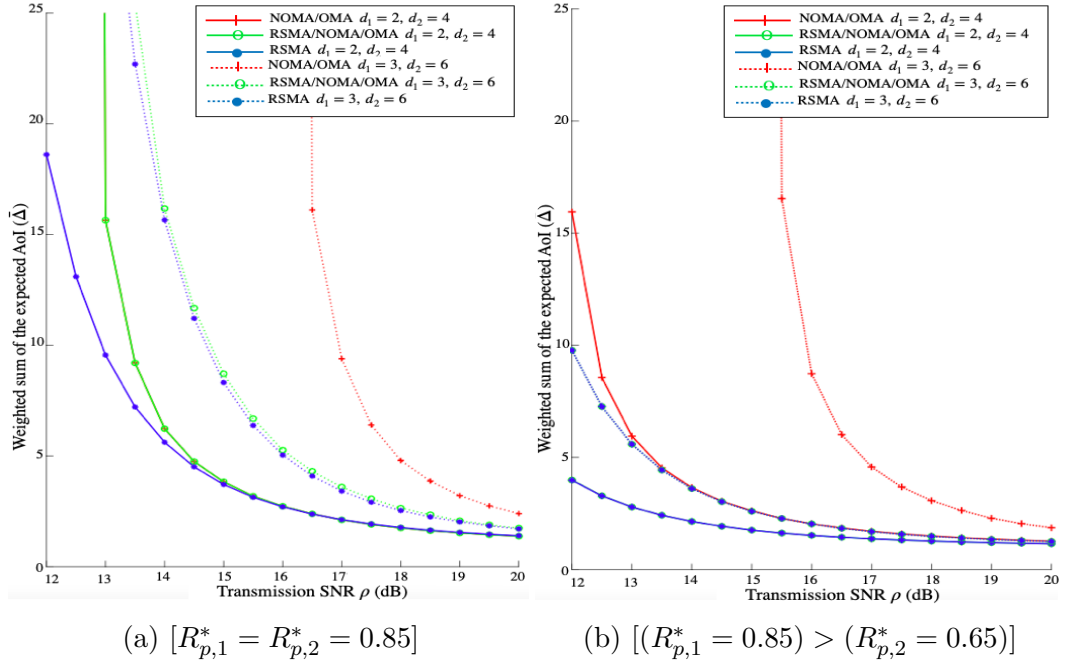


Figure D.10: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_2 = 0.7) > (w_1 = 0.3)]$, equal common target rates, far user's private target rate changing]

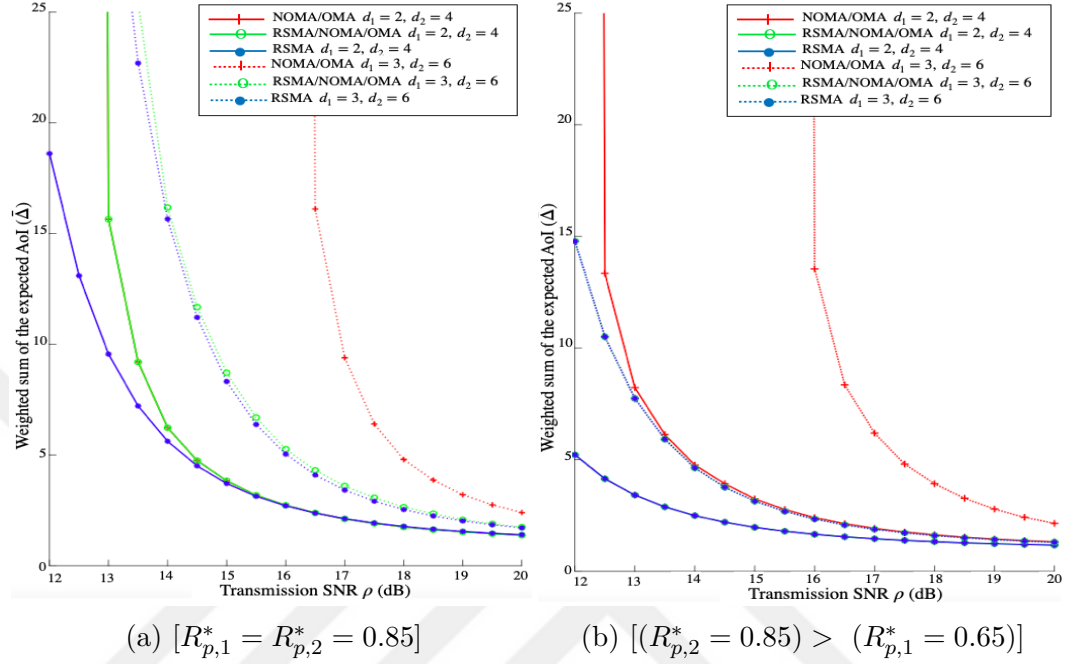


Figure D.11: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(w_2 = 0.7) > (w_1 = 0.3)]$, equal common target rates, far user's private target rate changing

D.4 Additional Age-Energy Tradeoff Graphics for Equal Private Unequal Common Target Rates, and Unequal User Weights

In this scenario, impact of the user distance from BS on the performance metric, WSAoI, is studied, while keeping values of all other parameters as constant.

Age-energy tradeoff under unequal target rates and unequal user weights with equal private target rates while changing common target rates is investigated for different values for distances of users from BS, d_1 and d_2 . Simulation parameters and results for the simulations of the impact of user distances from the BS on WSAoI for the first sub-scenario where the user distances are changed while keeping d_2/d_1 constant under unequal user weight distribution are shown in the Table D.4, and in Figure D.12 for $R_1^* > R_2^*$, $\{[w_1 > w_2], [w_2 > w_1]\}$ and in Figure D.13 for $R_2^* > R_1^*$, $\{[w_1 > w_2], [w_2 > w_1]\}$ for the scenarios with $R_{p,1} = R_{p,2} =$

Table D.4: Simulation parameters for age-energy tradeoff under equal private, unequal common target rates and unequal user weights

Parameter	Value
R_1^*, R_2^*	(1.0,0.8),(0.8,1.0)
$R_{p,1} = R_{p,2}$	0.65
$R_{c,1}, R_{c,2}$	(0.35,0.15),(0.15,0.35)
w_1, w_2	(0.7,0.3),(0.3,0.7)
N	10
SNR ρ dB	12, 13, 14, 15, 16, 17, 18, 19, 20
d_1, d_2	(2,4), (3,6)

0.65.

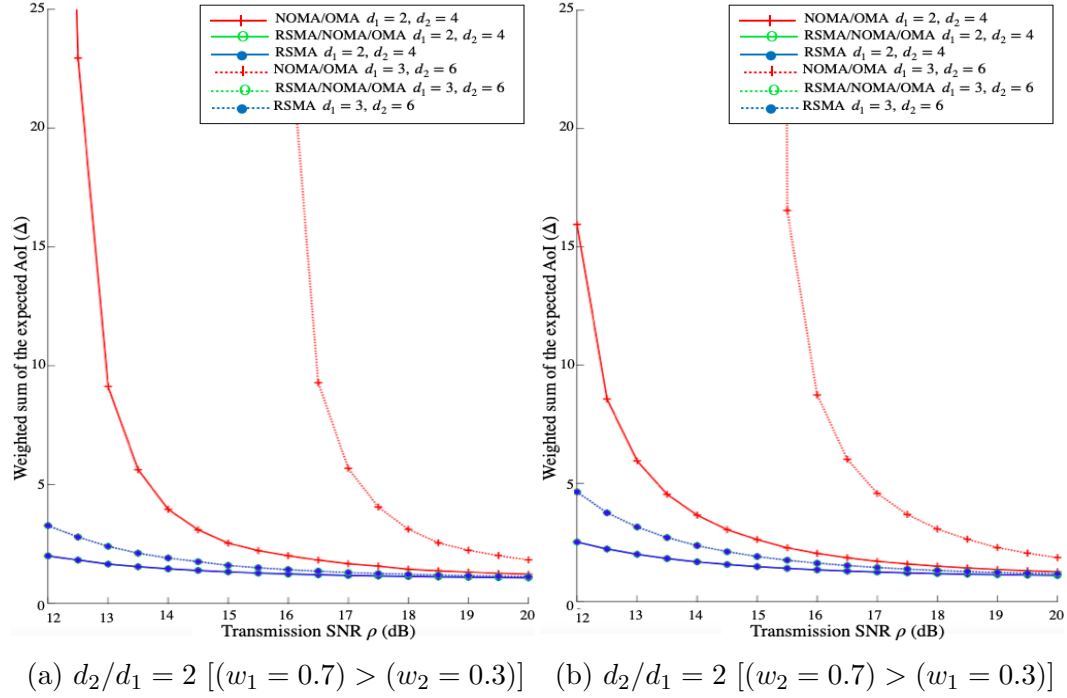


Figure D.12: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed $[(R_1^* = 1.0) > (R_2^* = 0.8), (R_{p,1}^* = R_{p,2}^* = 0.65)]$

Figure D.12 and Figure D.13 show that RSMA scheme outperforms NOMA/OMA schemes for both $R_1^* > R_2^*$ ($R_{c,1}^* > R_{c,2}^*$) and $R_2^* > R_1^*$ ($R_{c,1}^* > R_{c,2}^*$), for both user distances $\{(d_1 = 2, d_2 = 4), (d_1 = 3, d_2 = 6)\}$, and at all ranges of SNR (ρ) (0.12 - 0.20). It is also observed that both RSMA and RSMA/NOMA/OMA schemes take the same actions, and the related curves coincide.

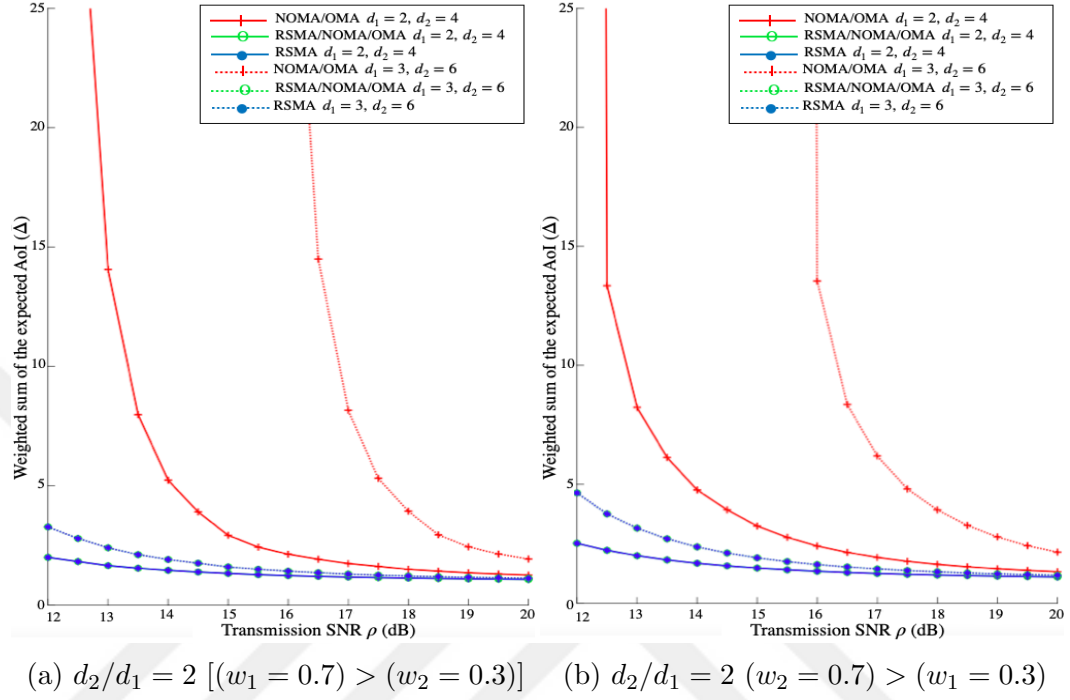


Figure D.13: Age-energy tradeoff for user distances $d_2/d_1 = \text{constant}$, distance values are changed [$(R_2^* = 1.0) > (R_1^* = 0.8)$, $(R_{p,1}^* = R_{p,2}^* = 0.65)$]

Comparing Figure D.6 with Figure D.12 show that, without changing the user weights and target rates, while keeping the user 2's private target rate constant, decreasing user 1's private target rate decreases WSAoI substantially. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher.

Similarly, comparing Figure D.7 with Figure D.13 show that, without changing the user weights and target rates, increasing user 2's private target rate while keeping the user 1's private rate constant decreases WSAoI. However, this observation is much obvious for the case where the user 1's weight is higher than the case where the user 2's weight is higher. Considering this observation and the observation given in the previous paragraph, it can be concluded that, without changing the user weights and target rates, decreasing one user's private target rate while keeping the other user's private target rate constant decreases WSAoI substantially.